

**Effort, turnover intention and meaningfulness: The
influence of Robotic Process Automation**

Kushal J. Singh

14449405

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ABSTRACT

With technological advancements reshaping the way they do business, organisations are determined to understand how their people, process and technology can complement each other to enable high performance. Driving increased effort levels and retaining top talent has become priority, since retention and effort influence positive outcomes. Robotic Process Automation (RPA) is encroaching into the work space of humans, restructuring their work and forcing them into intellectual domains that are more value-adding. However, creating synergy between man and machine will determine if effort and retention levels improve.

120 knowledge workers (n=120), whose nature of work ranged from routine and repeatable to abstract and improvisational, responded to an online survey regarding RPA's impact on their jobs. Using a quantitative approach, the study was focussed on understand whether RPA improved their work meaningfulness and what this meant for their effort levels and turnover intention.

Results from a correlation analysis indicated that RPA makes their work more meaningful and reduces their intention to turnover but has no effect on their effort levels, emphasizing the complex nature of discretionary behaviours. A mediated regression analysis further established that meaningfulness partially explains the link that existed between RPA and turnover intention, implying that other reasons may exist for improving retention levels within an RPA context.

KEYWORDS

Robotic Process Automation, discretionary effort, intention to turnover, meaningfulness, sensemaking

DECLARATION

I declare that this research project is my own work. It is submitted in partial fulfilment of the requirements for the degree of Master of Business Administration at the Gordon Institute of Business Science, University of Pretoria. It has not been submitted before for any degree or examination in any other University. I further declare that I have obtained the necessary authorisation and consent to carry out this research.

Kushal J. Singh

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LIST OF ACRONYMS

RPA – Robotic process automation

DE – Discretionary effort

ITT – Intention to turnover

EE – Employee engagement

HRD – Human resource development

EFA – Exploratory factor analysis

CFA – Confirmatory factor analysis

PCA – Principal component analysis

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CHAPTER 1: INTRODUCTION TO THE RESEARCH PROBLEM

1.1 Introduction

The demise of the capitalist system because of its success (Elliot, 1980) is an example of the Schumpeterian Paradox that was articulated by economist Joseph Schumpeter during the 1950's as "creative destruction" (p. 46). The phenomenon of creative destruction is the defining characteristic of all the industrial revolutions experienced to date where the equilibrium that each one had created was upset through the discontinuous change in technology. This has inevitably led to the demise of old industries, products, methods and techniques to give rise to the new (Elliot, 1980; Jensen, 1993; Nicholas, 2003; Senge, Carstedt, & Porter, 2001).

Creative destruction is being experienced once again, this time via the fourth industrial revolution, a period that is categorised by using large-scale automation and digitisation of processes to drive effectiveness and efficiency both within business and personal use while relying on internet-based technologies like the Internet of Things (IoT) (Moavenzadeh, 2015; Roblek, Mesko, & Krapez, 2016; Ross, 2018). From a business perspective, efficiencies as a result of digital technologies improve productivity and customer value. Hence organisations understand and appreciate the urgency in transforming their businesses using digital technologies (Ross, 2018).

Not embracing this creative destruction that the fourth industrial revolution brings can be detrimental to business, as was the classic case with Kodak during the mid-1990's. Kodak's inability to digitally evolve as an organisation resulted in their film-based camera business being heavily disrupted by the advent of digital photography (Shih, 2016). However, organisations like Lego, (Andersen & Ross, 2016) who were on the verge of bankruptcy in 2004 and Toyota, (Betancourt, Mooney, & Ross, 2015) who realised that the automobile ecosystem was changing, were able to leverage digital technologies, both in their product offerings and internal business processes, to reinvent themselves as a successful organisations.

Technological change is rapidly changing the way organisations conduct business and these changes are benefitting both customers and employees irrespective of the size of the organisation (Westerman & Bonnet, 2015). Internal innovation is critical to ensure long term business sustainability (Birkinshaw, Zimmermann, & Raisch, 2016). Robotic Process Automation (RPA), an example of how technology can

benefit employees, is a branch of cognitive technology (Davenport, 2011) that is designed to ultimately enhance internal business processes using task automation technology. Routine and repetitive, rule-based tasks are now being automated using RPA resulting in work-restructuring, a focus on abstract tasks that require cross-functional collaboration and increased human interaction, better designed work and skill utilisation and ultimately, process effectiveness and efficiency (Asatiani & Penttinen, 2016; Autor, 2015; Avasthy, 2019, Davenport, 2011; Davenport & Kirby, 2016; Lacity & Willcocks, 2015; Lacity & Willcocks, 2016; Lacity, Willcocks, & Craig, 2015; Lhuer, 2016; Mendling, Decker, Hull, Reijers, & Weber, 2018; Oldham & Fried, 2016; Willcocks, Lacity, & Craig, 2015; Willcocks, Lacity, & Craig, 2017). RPA is a relatively new phenomenon that has only recently been showing a steady rate of adoption by organisations (Agaton & Swedberg, 2018; Lacity et al., 2015). As such, understanding how to leverage technologies like RPA within the context of knowledge workers is important so that organisational performance can be improved.

1.2 Description of the problem

Knowledge workers are important contributors to organisational and customer value creation therefore it is critical to ensure that they are properly enabled to secure high levels of effort and productivity from them (Drucker, 1999). Knowledge workers require autonomy (Gambardella, Panico, & Valentini, 2015) optimised workplace design and processes (Davenport, Jarvenpaa, & Beers, 1996; Davenport, Thomas, & Cantrell, 2002), well-designed jobs that contribute to wellbeing (Oldham & Fried, 2016) and the appropriate application of technology since their technology and information demands vary depending on the type of work that they do (Davenport, 2011).

Knowledge workers perform work that is generally categorised as: (1) repeatable work, (2) improvisational work, (3) routine work and (4) judgement-oriented work (Davenport, 2011). Autor and Price (2013) and Autor (2015) suggest that routine and repetitive tasks are predictable hence easily automated and since an occupation or job is usually a combination of tasks (Autor, 2015; Mendling et al., 2018), automating the routine and repeatable work within jobs will increase effectiveness of executing abstract, improvisational or judgement-oriented work (Oldham & Fried, 2016).

Optimising the performance of knowledge workers implies maximising their engagement levels. Employees who experience high engagement levels exert 57% more effort in the work that they do, and demonstrate 87% lower turnover intention (Buchanan, 2004; Saks, 2006; Shuck, Reio, & Rocco, 2011) and extend themselves beyond what is required resulting in an overall organisational benefit (He, Zhu, & Zeng, 2014). High DE levels and a low ITT are positively related to organisational performance (Allen, Bryant, & Vardaman, 2010; Lloyd, 2008). Furthermore, a direct relationship exists between employee engagement (EE) and customer and organisational value (Harter, Schmidt, & Hayes, 2002).

Work meaningfulness, a dimension of EE together with availability and safety (Kahn, 1990), is the largest contributor to EE (May, Gilson, & Harter, 2004). Meaningful work is significant (Rosso, Dekas, & Wrzesniewski, 2010) and enriching and positive (Bailey, Madden, Alfes, Shantz, & Soane, 2017). Meaningfulness is enabled by well-designed, autonomous work (May et al., 2004), person-job fit (Resick, Baltes, & Shantz, 2007) and favourable work interactions (Lips-Wiersma & Morris, 2009) and is derived through a process of sensemaking (Aguinis & Glavas, 2019). Apart from being the largest contributor to EE (May et al., 2004), meaningfulness also improves one's psychological well-being (Arnold, Turner, Barling, Kelloway, & McKee, 2007) and creates a level of cohesiveness between the organisation and employee through organisational identification (Pratt, Rockmann, & Kaufmann, 2006).

As described above, given RPA's capability to replace human-performed, routine and repetitive, rule-based tasks, and the different types of work that knowledge workers perform, introducing RPA into the work of a knowledge worker should result in work-restructuring where an increased focus on abstract tasks that require cross-functional collaboration and increased interaction enabling higher value creation will ensue. Furthermore, work will be better designed, and skill utilisation optimised resulting in increased effectiveness and efficiency, from both a knowledge worker and organisational perspective. Therefore, while the current body of research regarding knowledge workers, EE and its outcomes (including work meaningfulness) are extensive, they fail to provide an understanding of how emerging technologies like RPA influence organisational outcomes that drive performance such as DE and ITT, particularly of knowledge workers, who are organisational value creators.

1.3 Purpose of the research

The purpose of this research is to understand how an emerging technology in the form of RPA, influences voluntary work outcomes of DE and ITT, that are strongly associated with organisational performance, of knowledge workers. In other words, given their importance, does the introduction of RPA within the work of a knowledge worker improve their work design such that their productivity is increased leading to higher levels of DE and ITT.

Therefore, the objectives of this research are to:

- Understand the relationship between RPA and work meaningfulness,
- Understand the relationship between RPA and DE,
- Understand the relationship between RPA and ITT and
- Understand the degree to which meaningfulness explains any relationship that may exist between RPA and DE and ITT so that work meaningfulness can be enhanced.

1.3.1 Business rationale

Firstly, given the business technologies that the fourth industrial revolution brings, organisations understand and appreciate the urgency in leveraging digital technologies (Ross, 2018) since internal innovation is critical to ensure long term business sustainability (Birkinshaw et al., 2016).

The core of this study is focussed on establishing whether (1) the introduction of RPA can improve DE levels and reduce the ITT of knowledge workers, who are considered the key source of innovation and organisational success (Drucker, 1999) and (2) work meaningfulness is responsible for the relationship that may exist between RPA and these organisational outcomes. From a practical perspective, management would want to understand how RPA can be leveraged to improve DE levels since it is considered a part of the organisational performance domain (Lloyd, 2008) and positively impacts organisational performance (Brown & Leigh, 1996).

Staff turnover impedes organisational performance (Park & Shaw, 2013; Trevor & Nyberg, 2008) and can directly cost organisations between 90% and 200% of annual salaries (Allen et al., 2010). In addition to this, intangible separations costs which

have a long-term impact, are indirectly damaging to an organisation from a qualitative perspective. This includes loss of institutional knowledge, disruptions to continuity of work, potential loss of clients and decreased quality of work output in the absence of key staff (Allen et al., 2010). These direct and indirect impacts are the reason why organisations initiate retention strategies to retain key staff that the organisation would not want to lose. Therefore, understanding how RPA influences a knowledge workers intention to leave is important.

Should meaningfulness be integrally connected with RPA in its relationship with DE and ITT, then this will have human resource development (HRD) implications since work will have to be redesigned to secure high levels of meaningfulness (Bailey et al., 2017). Furthermore, when routine tasks are replaced in its entirety by automation, highly skilled knowledge workers should either have their existing jobs redesigned or they should be repositioned in the organisation for their skills to be leveraged. In addition to this, knowledge work that is made up of both routine and abstract tasks, the replacing of routine tasks will free up time to focus on abstract tasks and again, job redesign or employee repositioning should occur. RPA catalyses this job redesign or employee repositioning within the organisation.

1.3.2 Academic rationale

Relative to meaningfulness, DE and ITT, RPA is a new concept that is still in an infancy stage from an academic perspective (Agaton & Swedberg, 2018; Lacity et al., 2015), with limited academic literature to support it resulting in the researcher having to develop a measurement scale to quantify RPA's influence on meaningfulness, DE and ITT within this study (refer to Section 4.6). Furthermore, as discussed in Section 1.2, current research on EE, meaningfulness and organisational outcomes fail to provide an understanding of how emerging technologies like RPA will influence organisational outcomes such as DE and ITT, particularly of knowledge workers.

Current literature on the impact of automation on jobs either take an occupational view (Frey & Osborne, 2017) or a task-based view that considers automation as complementary (Acemoglu & Restrepo, 2016; Arntz, Gregory, & Zierahn, 2016; Autor, 2015; Brandes & Wattenhofer, 2016). These studies do not consider the

following: (1) the distinction between automation that perform physical tasks and those that perform digital tasks (Davenport & Kirby, 2016) and (2) knowledge work as opposed to manual work (Drucker, 1999). This study makes a theoretical contribution to automation specifically from a digital task perspective on the work performed by knowledge workers. Furthermore, as opposed to understanding RPA with the broad context of EE, meaningfulness has been selected to focus the proposed theoretical framework on a dimension that contributes the most to EE (May et al., 2004).

1.4 Research scope

The scope of this research is limited to knowledge workers, as opposed to manual workers, who have had tasks within their jobs impacted by RPA (digital task automation) within corporate organisations across any geographical context. Essentially, the target population are office workers who have had routine and repetitive tasks within their jobs replaced by RPA.

1.5 Structure of the research

This research is structured as follows:

Chapter 1: Introduces the concept of RPA, articulates the research problem and clarifies the business and academic rationale.

Chapter 2: Examines what is already known regarding RPA, meaningfulness, DE and ITT. It uses this theory base to substantiate the research hypotheses put forward and proposes a theoretical framework

Chapter 3: Consolidates the research hypotheses that was developed from the literature review in chapter 2, these hypotheses will be used to test and prove the proposed theoretical model that governs this study.

Chapter 4: Describes the methods and procedures that were used to test the research hypotheses in chapter 3 together with a discussion on the development of the RPA measurement scale.

Chapter 5: Presents the results from the research hypotheses developed in chapter 3 that were tested using the methods and procedures in chapter 4.

Chapter 6: Discusses the results that were reported in chapter 5 and contextualises it within the literature from chapter 2.

Chapter 7: Outlines the principal findings from this research together with management implications, research limitations and proposals for future research.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

The purpose of this research was to understand how an emerging technology in the form of RPA, influenced voluntary work outcomes of DE and ITT, that are strongly associated with organisational performance, of knowledge workers.

Firstly, the evolution of work together with overarching theme of cognitive technology is examined where the underlying principles of RPA, a relatively new phenomenon that is still in its infancy stages from an academic and practical perspective, is discussed. RPA, a technological domain within cognitive technology, is defined and its impact on work is examined within the concept of knowledge work and the drivers of knowledge worker productivity.

Secondly, the psychological construct of meaningfulness is discussed where it is described in terms of its dimensions, its derivation and its outcomes, one of which is EE. The importance of EE and seminal literature around the construct is discussed where it is distilled into its psychological dimensions of meaningfulness availability and safety. The core outcomes of engagement, DE and ITT are presented where the implications of their voluntary nature are articulated within the context of meaningfulness. Research hypotheses were systematically derived and positioned within the literature as enough academic basis was created to support it and all mediation tests were substantiated using literature.

Finally, the chapter concludes when a proposed theoretical model that formed the basis of this research was put forward. In sum, this theoretical model proposed that RPA's potential relationships with DE and ITT was explained by work meaningfulness. This proposed theoretical model was together with the research hypotheses are then consolidated in Chapter 3.

2.1 The evolution of work

2.1.1 An overview of the various industrial revolutions

According to Jensen (1993) and De Vries (1994), the distinguishing features between the first and second industrial revolutions were the shifts from labour intensive to capital intensive production that resulted in exponential growth in productivity, improved standards of living and a change in economic behaviour. The first industrial revolution was dominated by the application of alternative forms of energy to production and transportation methods as coal substituted wood as a key source of energy (Jensen, 1993; Senge et al., 2001; Wrigley, 2013).

The second industrial revolution was broadly described as an era where mass production led to decreased consumer prices and production costs, and distribution, telecommunication and a variety of transportation methods emerged. Further advancements in the form of business management practices, technology, taxes, the system of capitalism, global trade and excess capacity (resulting from the stockpiling of goods that were previously produced with old technology) were the hallmarks of the third industrial revolution. Due to the extent of technological advancements, the impact of the third industrial revolution on the financial, product and labour markets were largely unknown at the time (Jensen, 1993).

The Schumpeterian paradox that described the demise of capitalism because of its success (Elliot, 1980) was articulated by Joseph Schumpeter as creative destruction, a concept that resonated with the core characteristics of the industrial revolutions experienced this far (Nicholas, 2003; Senge et al., 2013). The various iterations of industrial revolutions had upset the equilibriums they have created, and each have brought about discontinuous change in technology that have led to the demise of old industries, products, methods and techniques to give rise to the new (Elliot, 1980; Nicholas, 2003; Senge et al., 2013).

The fourth industrial revolution, or industry 4.0 as it is sometimes referred to, is basically categorised as using internet technologies, large scale automation and digitisation to drive effectiveness and efficiency both within business and personal use (Roblek et al., 2016). Using the capability of the internet, the Internet of Things (IoT) connect devices and machinery together which enables communication of key

data thereby optimising their functionality and outputs (Löffler & Tschiesner, 2013). Therefore, technological progress is the key theme of the industrial revolutions.

2.1.2 An overview of technology's impact on work

In 2000, only 2% of the United States labour force was employed in the agricultural sector as opposed to 41% in 1900 due to advancements in technology and automation (Autor, 2014). Initial research performed to understand how automation impacted work (Frey & Osborne, 2017) opened the discussions around automation and its impact on labour where it was concluded that occupations consisting of tasks that are well defined and made up of specific steps can be replicated by computer systems executing advance algorithms. Tasks that required judgement, intuition, collaboration and deep expertise were difficult to automate and remained within the domain of humans (Frey & Osborn, 2017).

In a study of 702 detailed occupations categorised according to their ease of automation reported that almost half of the jobs in the United States labour market may become fully automated requiring impacted employees to acquire skills to adopt more abstract work (Frey & Osborne, 2017). However, the subjective methodology of the study was criticised by other scholars on the basis that it concluded holistically on *occupations* as opposed to *tasks within occupations* as being automated (Acemoglu & Restrepo, 2016; Arntz et al., 2016; Brandes & Wattenhofer, 2016). Tasks within jobs that cannot be automated become complemented by automation (Autor, 2015) and this was a major limitation of their study since workers within the same occupations may perform different tasks. As a result, subsequent work performed on the foundations of Frey and Osborne (2017) found that workers in occupations categorised as high risk are in fact less susceptible to automation since they also perform a substantial amount of non-routine tasks that are unable to be automated (Arntz et al., 2016; Brandes & Wattenhofer, 2016). This was concluded by not only looking at jobs, but by analysing the tasks that make up these jobs. Therefore, the focus should be on examining tasks within jobs that are at risk of automation including training and retraining for this climate of change, rather than focussing on how entire jobs will be lost to automation (Acemoglu & Restrepo, 2016; Arntz et al., 2016; Autor, 2015; Brandes & Wattenhofer, 2016; Kim, Kim, & Lee, 2017).

Furthermore, the distinction between tasks and skills are important. A task is an element of a job that produces an outcome whereas a skill is the capability of that person in executing on the tasks within a job (Autor & Price, 2013). According to Autor and Price (2013), technology will impact tasks and skills differently and will eventually determine what type of skills are required to execute on a job.

Kim's et al. (2017) study of job automation is positioned between Frey and Osborne (2017) and Acemoglu and Restrepo (2016). Their study, which takes an occupational view, suggests that technological advancement will lead to the creation of new technical jobs that will create future employment for the labour force (Kim et al., 2017). The positions of Acemoglu and Restrepo (2016), Arntz et al. (2016), Autor (2015) and Kim et al. (2017) on the automation and skill debate echo's the Schumpeterian paradox of creative destruction where the equilibrium that was created in the job market prior to task automation was disrupted by automation and will eventually reach a point of equilibrium again.

2.2 Cognitive technology

Cognitive is derived from the word *cognition* which very rudimentarily describes the process of how an individual will think, process and perceive knowledge. Similarly, cognitive technology uses "knowledge, perception, judgment, and the wherewithal" (Davenport & Mahidhar, 2018, p. 20) to execute on and achieve tasks that were previously only able to be performed by humans. Cognitive technology can be broadly categorised into 4 types that are ranked according to intelligence and capability (Davenport & Kirby, 2016):

Table 1: Cognitive technologies: levels of intelligence

TASK TYPE	LEVELS OF INTELLIGENCE			
	SUPPORT FOR HUMANS	REPETITIVE TASK AUTOMATION	CONTEXT AWARENESS AND LEARNING	SELF-AWARENESS
Analyze Numbers	Business intelligence, data visualization, hypothesis-driven analytics	Operational analytics, scoring, model management	Machine learning, neural networks	Not yet
Analyze Words and Images	Character and speech recognition	Image recognition, machine vision	IBM Watson, natural language processing	Not yet
Perform Digital Tasks	Business process management	Rules engines, robotic process automation	Not yet	Not yet
Perform Physical Tasks	Remote operation of equipment	Industrial robotics, collaborative robotics	Autonomous robots, vehicles	Not yet

Adapted from: “Just how smart are smart machines?” by T. Davenport and J. Kirby, 2016, *MIT Sloan Management Review*, 57(3), p. 23. Copyright 2016 by Massachusetts Institute of Technology.

The term ‘robotic’ is generally associated with a mechanical robot performing tasks within an industrial context. Davenport and Kirby (2016) makes a distinction between robots that perform physical tasks and those that perform digital tasks. Both physical and digital task automation are a subset of **repetitive task automation** which is a rules-based automated decision-making process that generally relies on an algorithm. Physical task automation refers to an actual mechanical robot, controlled by a computer, that performs physical tasks that were previously performed by a human. For example, a robot that performs welding on automobile chassis on a production line that was previously welded by a human. Digital task automation refers to the automation of administrative tasks and decisions where a robot can navigate through a business process and make basic decisions based on simple, predefined business rules and logic (Davenport & Kirby, 2016) just as a human would have done. Therefore, as a computer software solution, a ‘robot’ within an RPA context refers to a software license within a computer system (Lacity & Willcocks, 2016).

Repetitive task automation is ranked second among cognitive technologies according to intelligence (see table 1). **Context awareness and learning technology** is of superior intelligence to repetitive task automation because of its ability to learn and improve its performance (Davenport & Kirby, 2016). For example,

machine learning, which is a type of context awareness and learning technology within the cognitive domain in figure 1, can recognise patterns within data, identify structures of a complex nature that was not initially defined and predict unique attributes from data (Mullainathan & Spiess, 2017). Repetitive task automation does not have this capability.

2.2.1 Robotic Process Automation (RPA)

RPA is a type of repetitive task automation within the cognitive technology domain (Davenport & Kirby, 2016) and is categorised as an emerging technology. It has limited academic literature to support it however, use of RPA technology in business is increasing year on year (Agaton & Swedberg, 2018, Lacity et al., 2015). Replacing manual human work by machinery and automation has been one of the key characteristics of the industrial revolutions (Autor, 2014) and technology driven by computer systems can perform symbolic processing (Autor, Levy, & Murnane, 2003). This enables it to “calculate, store, retrieve, sort, and act upon information” (Autor et al., 2003, p. 5) and it is symbolic processing that has resulted in computer systems being able to replace routine tasks.

RPA is described as a type of business automation software that can replicate and perform digital tasks that were previously performed by a human and are suitable to be applied to processes based on predefined business rules that are simple, standardised and repetitive (Asatiani & Penttinen, 2016; Autor, 2015; Avasthy, 2019, Davenport, 2011; Davenport & Kirby, 2016; Lacity & Willcocks, 2015; Lacity & Willcocks, 2016; Lacity et al., 2015; Lhuer, 2016; Mendling et al., 2018; Oldham & Fried, 2016; Willcocks et al., 2015; Willcocks et al., 2017).

Drawing from the existing literature on RPA, the researcher proposed the following operational definition: RPA, a subset of repetitive task automation is the use of computer software that is designed, according to digital task automation, to execute high-volume, routine or repetitive tasks within a job that were previously performed by a human according to predefined business rules. With increasing workloads, RPA replaces the undesirable, mundane tasks which relieves pressure on employees (Lhuer, 2016) and eventually restructures existing work to allow employees to focus on more meaningful, strategic and value-adding work, including more human interactions that enhance social capital within organisations (Avasthy, 2019). In a

traditional RPA scenario, the program would produce outputs that would require a level of reasoning and judgement to be applied by a human in order to complete the exercise (Lhuer, 2016) and therefore works in a complementary fashion with humans (Autor, 2015). An example of steps that a robot would execute to complete a task is outlined below:

Table 2: A conventional RPA process

Steps for software robots to complete	
1.	Pick first incomplete transaction from the work queue (the transactions in the queue could have been formulated e.g. by receiving triggers, by reading a specific report, by accessing a specific web portal etc.).
2.	Launch application X.
3.	Enter specific (fixed or variable) value into a specific field.
4.	Click a specific button in an application.
5.	Read value in a specific location in application X and store it in variable Z.
6.	Launch application Y.
7.	(...)
8.	Enter variable Z into a specific field in application Y.
9.	If an error message is shown, store result about error in a report and move to step 12. Otherwise proceed to step 10.
10.	(...)
11.	Store result of a transaction in a report.
12.	Pick next transaction and return to step 3.

Adapted from: "Turning Robotic Process Automation into Commercial Success – Case OpusCapita" by A. Asatiani and E. Penttinen, 2016, *Journal of Information Technology Teaching Cases*, 6(2), p. 7. Copyright 2016.

The software solution can take the form of desktop RPA, a very basic solution that uses established technologies like macros and screen scraping to record the actions of a user for replication but lacks a basic level of intelligence (Willcocks et al., 2017) or a more advanced version that is deployed on a central server as opposed to a desktop, using business rules and inferences called 'cognitive automation' or enterprise RPA with basic levels of intelligence (Davenport & Kirby, 2016; Lacity & Willcocks, 2016; Willcocks et al., 2017). RPA has 3 unique characteristics when compared to traditional software solutions (Lacity & Willcocks, 2016):

RPA is easily configurable: writing a desktop RPA program does not require specialised software programming skills. It functions on the premise of graphically representing a business process where icons that represent steps within the business process to be automated are linked together creating an RPA process flow.

The code on which the software runs is generated by the software program itself and not written by any software developer and desktop RPA can be configured by an end user with minimal training

RPA is non-invasive: it interacts with other enterprise software solutions in the same way that a human does and does not require the development of additional platforms or interfaces to operate. The robot will have its own network domain username and password and will access an enterprise system through the presentation layer just like a human user would.

RPA meets enterprise-safety standards: the solution offers security, scalability and auditability which are basic requirements for business continuity and statutory compliance.

Practical application of RPA yields substantial returns and enhances business performance. A case study of RPA implementation at a publicly traded, technology and procurement company (Willcocks et al., 2015) revealed that 27 robots deployed across 14 processes resulted in cost savings of up to 30% per process. Other benefits realised were improved service levels and turnaround times, higher degrees of compliance and collaborative delivery between humans and robots due to the complementary nature of RPA (Autor, 2015). Another case study of RPA application at a large telecommunications company (Lacity et al., 2015) revealed that 160 robots deployed across 15 core processes yielded exponential returns on investment including the benefits of improved accuracy, turnaround times and collaborative delivery between humans and robots.

However, complementary employee experience is key to the effective functioning of RPA (Avasthy, 2019). Independent research by consulting firms report that 66% of employees confirm that RPA restructures tasks within their existing work and 60% confirm that RPA enables them to shift their focus onto more meaningful tasks including greater levels of human interaction and relationship building (Avasthy, 2019). Even though RPA is not positioned to replace jobs but rather restructure and complement existing tasks within a job (Autor, 2015), employees view RPA as a threat to their employment (Asatiani & Penttinen, 2016) and as such, the implementation of RPA should be performed delicately, using a structured change management approach to ensure that any concerns by employees are handled sensitively and does not erode their morale.

2.2.2 RPA within the context of knowledge work

Knowledge work is defined as “the use of knowledge in the workplace” (Kelloway & Barling, 2000, pg. 9) where there is an element of discretion and judgement when executing tasks (Drucker, 1999). Knowledge work is best understood by juxtaposing it against its opposite – manual work, which is work that is of a physical nature and always provides defined instructions as to how a task should be executed (Drucker, 1999). Knowledge work creates organisational and customer value therefore it is critical for organisations to ensure that knowledge workers are properly enabled to secure high levels of effort and productivity from them (Drucker, 1999).

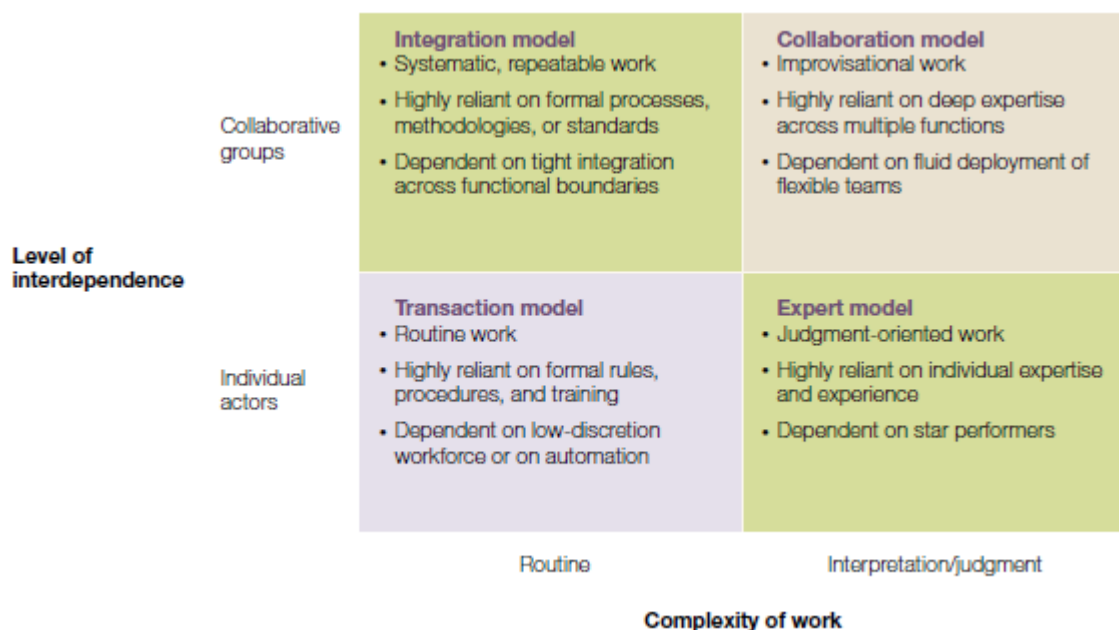


Figure 1: Knowledge worker job types

Adapted from: “Rethinking knowledge work: A strategic approach,” by T. Davenport, 2011, *McKinsey Quarterly*, 1(11), p. 9. Copyright 2011 by McKinsey & Company.

As per Figure 1 above, knowledge work types can be categorised as (1) repeatable work, (2) improvisational work, (3) routine work (4) judgement-oriented work (Davenport, 2011) and some categories of knowledge work are dynamic in nature with numerous deliverables requiring a degree of autonomy to be effectively and efficiently completed (Gambardella et al., 2015). Management style, organisational structure and workplace design influence knowledge worker performance (Davenport et al., 1996; Davenport et al., 2002) and information and technology

solutions should be provisioned to the knowledge worker based on the complexity of the task and interdependence that is required to complete it (Davenport, 2011) such that performance and productivity is optimised.

Since their demands vary based on work type, Davenport (2011) proposes 2 methods of technology application for knowledge workers: (1) structured provision technologies (workflow or automation technologies) or free-access approach (unlimited access to internet-based information). For example, routine tasks performed by a knowledge worker, which is usually simple and depends on low levels of judgement and discretion, will benefit from automation technologies like RPA. As task complexity and interdependence increase, a degree of judgement, improvisation and cross-functional collaboration is required and as such, free access technology approaches become more viable to enable meaningful work and improved productivity (Davenport, 2011).

Autor (2015) and Autor and Price (2013) categorised tasks according to their nature and suggested that routine and repetitive tasks are predictable, can be easily coded according to the rules that predict it and therefore easily automated. Tasks that require a level of professional judgement, expertise, analytical capability or intuition are referred to as *abstract* and tasks that require personalisation or “situational adaptability” or improvisation (Autor, 2015, pg. 12) are referred to as *manual*. Abstract and manual tasks, as per their nature, cannot be predicted and therefore are not easily solvable and as a result, not easily automatable (Autor et al., 2003).

Therefore, by triangulating Autor’s (2015), Autor and Price’s (2013) and Davenport’s (2011) knowledge work types, one can assume that the transaction and integration model, that consist of repeatable, repetitive tasks that are reliant on predefined business rules requiring very little or no collaboration, are easy to automate. The tasks from these models can be collectively referred to as *routine tasks*. Tasks in the expert and collaboration model, that require judgement, cross-functional collaboration and expertise, are difficult to automate. These tasks can be collectively referred to as *abstract tasks*. Table 3 below consolidates this view and proposes a broad categorisation for referring to these different types of work.

Table 3: Nomenclature for task types

Automation Viability	Work Model	Broad Categorisation
Easy to automate	Transaction and integration	Routine tasks
Difficult to automate	Expert and collaboration	Abstract tasks

Adapted from: "Rethinking knowledge work: A strategic approach," by T. Davenport, 2011, *McKinsey Quarterly*, 1(11), p. 9. Copyright 2011 by McKinsey & Company.

Occupations or jobs are usually a combination of tasks (Mendling et al., 2018) and automating the routine tasks will streamline the job and increase a knowledge workers' ability in performing abstract tasks (Autor, 2015) since well-designed jobs contribute to employee wellbeing and effectiveness (Oldham & Fried, 2016). The researcher's development of Table 3 above based on the knowledge work types (Davenport, 2011) and the viability of task automation based on its nature (Autor, 2015; Autor & Price, 2013) will be used as a basis for task definition such that going forward in this study, any tasks that are routine, systematic and repeatable in nature that rely on formal rules and procedures will be referred to broadly as **routine tasks**. Any tasks requiring improvisation or judgment that rely on expertise cross functional collaboration will be referred to broadly as **abstract tasks**. Consequently, the term RPA within this study will represent **the degree to which tasks within a job are impacted by automation**.

2.2.3 Summary of capability: RPA

From a review of the above literature, RPA can replace routine tasks within a job and allows a knowledge worker to focus on abstract tasks that require intuition, judgement, expertise or cross-functional collaboration. By replacing routine tasks, it allows the restructuring of work, improving its design and enabling improved skill utilisation during the execution of abstract tasks together with enhancing employee interaction that may be required for abstract tasks. It enables more effective and efficient exception handling and decision making when decisions are based on RPA

outputs. It improves person-job fit through effective skill utilisation and as a result, enhances employee self-perception and perceived significance of the work being performed (Asatiani & Penttinen, 2016; Autor, 2015; Avasthy, 2019, Davenport, 2011; Davenport & Kirby, 2016; Lacity & Willcocks, 2015; Lacity & Willcocks, 2016; Lacity et al., 2015; Lhuer, 2016; Mendling et al., 2018; Oldham & Fried, 2016; Willcocks et al., 2015; Willcocks et al., 2017).

2.3 Meaningfulness

In the general sense, when a situation is worthwhile enough in committing personal resources to meet its demands then that situation can be referred to as meaningful (Lips-Wersma & Morris, 2009). Attaining a level of meaningfulness in life is partly enabled by doing meaningful work since work makes up an integral part of one's life (Aguinis & Glavas, 2019).

From a work perspective, meaningfulness is defined differently by scholars. Meaningful work is congruent with a sense of reward, personal growth and development (Kahn, 1990), "the value of a work goal or purpose, judged in relation to an individual's own ideals or standards" (May et al., 2004, p. 14), aligned to the personal value system of the employee (Renn & Vandenberg, 1995), is enriching and contributes positively to the employee and organisation (Bailey et al., 2017), work which has a purpose that exceeds its outcomes (Arnold et al., 2007) or work "which is generally meaningful, valuable and worthwhile" (Hackman & Oldham, 1975, pg. 162).

Meaningfulness should not be confused with the concept of meaning (Rosso et al., 2010) and is often erroneously used interchangeably in academic literature. The word meaning, although derived from meaningfulness, has a different definition to meaningfulness. An experience will have meaning when an individual is able to make sense of it (Rosso et al., 2010) and the process of deriving meaning from experiences is referred to as sensemaking (Aguinis & Glavas, 2019). "Intraindividual, intra-organisational and extra-organisational" (pg. 9) "sensemaking factors" (pg. 2) are attributes that individuals use within the sensemaking process to attribute meaning to experiences. Therefore, introspection (intra-individual), leadership and work environment (intra-organisational) and impacted stakeholders (extra-organisational)

give meaning to work experiences. However, meaning alone does not make an experience meaningful (Rosso et al., 2010) but how *significant* an experience is for an individual does. Since significance is subjective, meaningfulness will vary among individuals. Meaningfulness implies that the eventual outcome is positive therefore meaningful work is both significant and positive for an individual (Rosso et al., 2010).

Drawing from the array of definitions of meaningfulness, the researcher has proposed the following operational definition of meaningfulness that will be used within the context of this study as **significant** (Rosso et al., 2010), **enriching and positive work** (Bailey et al., 2017) that is derived through a process of **sensemaking** (Aguinis & Glavas, 2019).

2.3.1 Dimensions of meaningful work

Meaningful work is enabled by: (1) work tasks, (2) work roles, (3) work interactions and (4) organisational attributes (Bailey et al., 2017).

Work tasks: A job is usually a combination of tasks that, when performed sequentially, leads to an outcome (Autor, 2015; Mendling et al., 2018). Early research found that challenging, well designed work that enables creativity and autonomy influence meaningfulness (Kahn, 1990) and subsequent studies provided evidence that enriched jobs (well-designed, challenging and autonomous) enhanced meaningfulness (May et al., 2004). Kahn's (1990) dimension of psychological meaningfulness is rooted in Hackman and Oldham's (1976) Job Characteristics Model (JCM) that defined conditions for effective work and personal outcomes. The JCM provided evidence that effective skill utilisation, identifying with tasks and significant work predicted meaningfulness and subsequent research not only corroborated this predictive relationship but proved that meaningfulness explains why skill utilisation results in rewarding work (Renn & Vandenberg, 1995). Based on the underpinnings of the Job Demands and Resources (JD-R) model (Bakker & Demerouti, 2014), which asserts that job demands can be alleviated through job resources, job crafting (Petrou, Demerouti, & Schaufeli, 2018; Tim, Derks, & Bakker, 2016) is a technique initiated by employees to craft their jobs such that demands and resources align to achieve greater levels of person-job fit (e.g. improving job resources like autonomy and skills) and ultimately meaningfulness. Job crafting

occurs when employees modify (1) nature and number of activities of tasks within a job, (2) the perception of the job and (3) the interactions the employee has with others (Petrou et al., 2018). Job crafting should not be confused with job design, where an employee executes on tasks within a job that had already been redefined, reconfigured and redesigned by management and HRD teams (Tim et al., 2016).

Work roles: Influential work roles which are aligned to one's own favoured self-image and inclusive, dignified work interactions influences meaningfulness (Kahn, 1990). Therefore, the perception of one's work by others as being esteemed in stature and contributory to a system (Bailey et al., 2017) will reaffirm the work – self-image relationship and contribute to meaningfulness. Furthermore, fit theory (Resick et al., 2007) explains how job and personal alignment improves person-job or work role fit which contribute to meaningful work and other studies also affirmed that work role fit was shown to predict meaningfulness (May et al., 2004). Job crafting can also be used as a mechanism to influence perception, improve autonomy and align work to preferred self-image thereby improving meaningfulness (Petrou et al., 2018; Tim et al., 2016).

Work interactions: Work interactions (either internally with other employees or external stakeholders) enhances connectedness and social capital since people have an inherent need to be connected through work (Bailey et al., 2017). As such, meaningful work is derived from a sense of belonging, interdependence and value sharing that creates bonds with others and articulates a common purpose (Lips-Wiersma & Morris, 2009). Aguinis and Glavas (2019) used the concept of Corporate Social Responsibility (CSR) (explained further in Section 2.3.2) to articulate that the degree of meaningfulness derived from work is dependent on the interactions with internal and external stakeholders.

Organisational attributes: Meaningful work relies on an organisational system that contextualises what is important and valuable based on institutionalised norms and an embedded culture (Stein, Wagner, Tierney, Newell, & Galliers, 2019). Organisations can exert strong influences on employees and alter their perceptions on what they interpret as meaningful or not (Bailey et al., 2017) and therefore have a responsibility to ensure that internal systems, processes and norms inspire meaningful work (Stein et al., 2019). Building on this rationale, organisational fit will therefore be important to finding meaningfulness and person-organisation fit is achieved when either of the following criteria are met (Resick et al., 2007): one party

provides the other party with what they need (complementary fit) attributes between the parties are common (supplementary fit).

2.3.2 Deriving meaningfulness

Individuals use sensemaking as a mechanism to create consistency and logic in paradoxical contexts within which they operate. Using sensemaking as a mechanism, Aguinis and Glavas (2019) adopted the self-regulating organisational practice of Corporate Social Responsibility (CSR) to demonstrate how meaningfulness can be derived from work. CSR, defined as organisational actions subscribing to the triple bottom line philosophy where environmental, social and economic factors are considered to ensure sustainability (Mitchell, Curtis, & Davidson, 2012), often have non-financial outcomes. Furthermore, by its nature, CSR creates “tensions and social dilemmas” among employees executing them (Aguinis & Glavas, 2019, p.8). It increases the scope of employees’ work into the social and environmental domains and external stakeholders, who are typically beneficiaries of CSR initiatives, contribute to the ambiguity of what needs to be accomplished. Using the sensemaking process, employees are able improve the meaningfulness of work when dealing with contexts such as CSR initiatives.

The following model outlines the sensemaking process which enables one to derive meaningfulness through work from a given stimulus (Aguinis & Glavas, 2019):

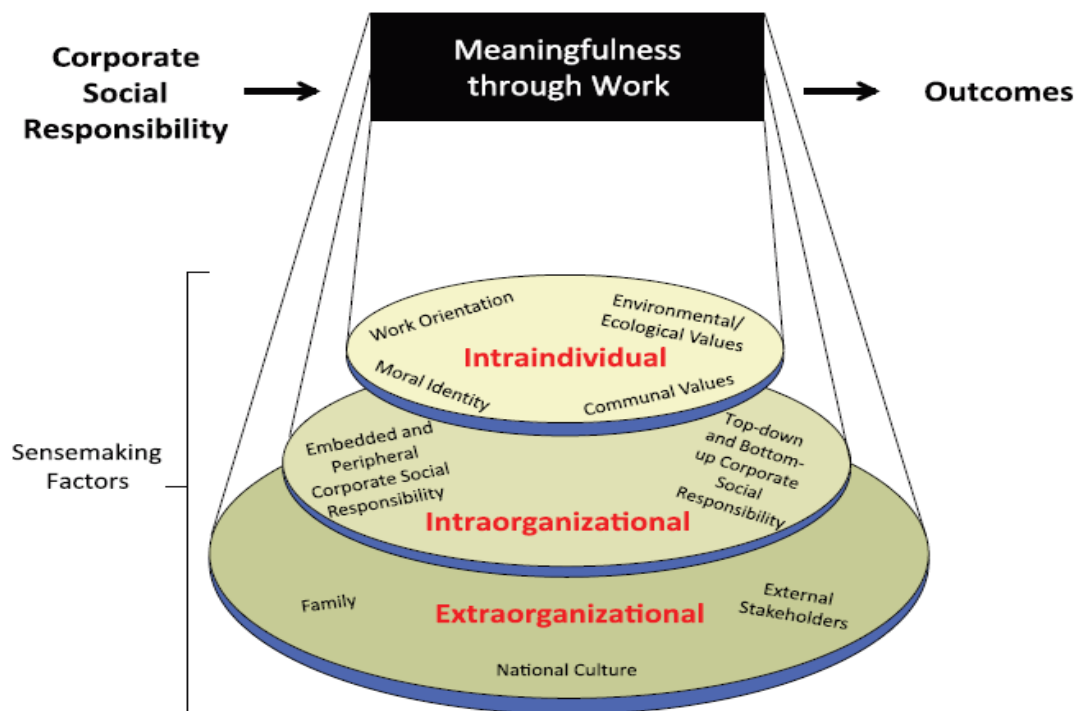


Figure 2: Sense making process

Adapted from: "On Corporate Social Responsibility, Sensemaking, and the Search for Meaningfulness Through Work," by H. Aguinis and A. Glavas, 2019, *Journal of Management*, 45(3), p. 9. Copyright 2019.

The model depicted above explains how meaningfulness can be attained through work within a paradoxical and ambiguous CSR context. The model, together with the sensemaking factors, is customised to fit a CSR context however, the principal on which the model operates can be applied universally.

Within the *intra-individual* sensemaking factor, the **work orientation** dimension is the largest contributor to meaningfulness and describes how the interplay between job orientation (driven by monetary rewards), career orientation (driven by career enhancement) and calling orientation (driven by the need to contribute) define the overall type of work orientation when performing ambiguous work. This will enable alignment to between self and work (Bailey et al., 2017; Kahn, 1990) and task significance (Hackman & Oldham, 1976; Rosso et al., 2010) to be established. Even though these orientations are related, Aguinis & Glavas (2019) suggest that a singular dominant orientation typically emerges. Inputs into this sensemaking factor would potentially feed from the work tasks, roles and interactions dimensions of meaningful work (Bailey et al., 2017) that would have been redefined and

restructured as a result of RPA (Avasthy, 2019, Davenport & Kirby, 2016; Lacity & Willcocks, 2016; Willcocks et al., 2015). From a work task perspective, RPA will enable a greater focus on abstract tasks resulting in greater levels of skill utilisation, improved levels of autonomy and more delineated work. From a work roles perspective, since greater levels of skill utilisation is demonstrated, work significance improves as perceived work contribution increases. This results in improved employee self-perception of work and perception by others of the work the employee is performing is improved. From an interaction perspective, the focus on abstract tasks will increase cross-functional collaboration resulting in greater interaction with other employees.

The *intra-organisational* sensemaking factor, which refer to organisational systems and practices that define and drive culture to influence the sensemaking process (Aguinis & Glavas, 2019) suggest that practices that are embedded within an organisation as opposed to superficially implemented will underpin the perception of culture as enabling meaningful work. From an RPA and technology perspective, understanding and appreciating the urgency in leveraging digital technologies (Ross, 2018) is key to embedding a digital culture since internal innovation is critical to ensure long term business sustainability (Birkinshaw et al., 2016). Therefore, organisations will drive the RPA agenda from upper management with urgency.

Extra-organisational sensemaking factors refer to the broader environment, that transcends organisational boundaries, that contribute to making sense of work (Aguinis & Glavas, 2019) and suggests how family (work-life balance), external stakeholders (work that influences people outside of the organisational boundaries) and national culture (collectivism versus individualism) will influence and determine what type of work is considered meaningful or not. Within the context of RPA, its capability to replace the undesirable, mundane tasks will relieve pressure on employees in times of increasing workloads (Lhuer, 2016) and will eventually restructures existing work to allow employees to focus on more abstract work that require greater levels of human interactions (Avasthy, 2019). Alternatively, employees may opt to use the extra time gained through work restructuring to improve work-life balance and indulge in extra-curricular activities that enhance work meaningfulness.

As discussed earlier, notwithstanding the CSR stimulus that was used by Aguinis and Glavas (2019) to demonstrate the functioning of their sensemaking model, its

applicability within an RPA context has been demonstrated and established by the researcher. The model can therefore be used within the context of this study to understand how meaningfulness can be derived from work tasks, roles, interactions and organisational attributes that have been impacted by RPA.

2.3.3 Outcomes of meaningfulness

The positive personal and organisational outcomes of meaningfulness are evident in literature (Arnold et al., 2007; Bailey et al., 2017; Hackman & Oldham, 1976; Kahn, 1990; May et al., 2004; Pratt et al., 2006; Renn & Vandenberg, 1995; Shuck et al., 2011). Work meaningfulness predicts improved work performance, job satisfaction, motivation and work attendance while reducing staff attrition (Hackman & Oldman, 1976). It explains why work inputs result in effective and rewarding outputs (Renn & Vandenberg, 1995), improves one's psychological well-being (Arnold et al., 2007) and creates a level of cohesiveness between the organisation and employee (Pratt et al., 2006).

Meaningfulness' strong relationship with EE is perhaps one of its most important outcomes since EE results in positive organisational outcomes (Kahn, 1990; Kumar & Pansari, 2015; Leiter & Maslach, 2003; Macey & Schneider, 2008; Rich, Lepine, & Crawford, 2010; Saks, 2006; Schaufeli & Bakker, 2004; Shuck et al., 2011; Shuck & Wollard, 2010). Initially conceptualised by Kahn (1990), he defined engagement as "...the harnessing of organisation members' selves to their work roles; in engagement, people employ and express themselves physically, cognitively, and emotionally during role performances" (p. 694). Engagement enables connections to others and the expression one's authentic self in the execution of work and suggests that disengagement is the disconnect of one's self from a "physical, cognitive, or emotional" perspective from the work that they do (p. 694). Engagement results from someone possessing high levels of energy, involvement in their tasks and self-efficacy (Leiter & Maslach, 2003) while another study characterised it by one having "vigour, dedication and absorption" (Schaufeli & Bakker, 2004, p. 295).

Work is an important element of one's life and being satisfied with work has a positive relationship with quality of life (Judge & Watanabe, 1993). Since the turn of the millennium, only 13% of employees worldwide and 32% within the United States were reported to be engaged (Mann & Harter, 2016). Business executives are trying

to understand how to increase the performance of their organisations by adopting a human capital approach through increasing EE levels (Macey, Schneider, Barbera & Young, 2011). Within the researcher's company of employment, a diversified multinational organisation employing almost 70,000 people globally, understanding how to improve EE levels to drive high performance and retention rates of employees have become of great importance to management across the group.

The organisational and individual benefits of EE are widely reported in literature (Harter et al., 2002; He et al., 2014; Huselid, 1995; Markos & Sridevi, 2010; Rich et al., 2010, Richman, 2006; Truss, Shantz, Alfes, & Delbridge, 2013). A human resource strategy with a strong EE agenda impacts organisations positively (Albrecht, Bakker, Gruman, Macey, Saks, 2015) and studies provide evidence that relationships between EE and organisational and customer value exist (Harter et al., 2002). Employees who experience high engagement levels are problem solvers who are cultural ambassadors (Richman, 2006), exert more effort and have reduced intentions to leave (Buchanan, 2004; Schaufeli & Bakker, 2004), and extend themselves beyond what is required to ensure organisational success (He et al., 2014). A high employee retention rate will have positive implications for re-hire and training costs (refer to Section 2.5.1 for the cost of employee turnover).

Kahn's (1990) study of engagement revealed 3 psychological dimensions that explained its existence: meaningfulness, safety and availability. **Meaningfulness** is detailed above however **Safety**, the second dimension of engagement, describes the consistent organisational environment that enables expression without the fear of prejudice and cites strong employee-manager relationships, leadership and supportive structures as examples that contribute to the safety. **Availability**, the third dimension of engagement, describes the physical and mental resilience needed by employees for high performance and is enabled by a strong physical state and being of sound mind.

Subsequent research empirically tested these 3 dimensions (May et al., 2004) to understand the extent to which each of them contributed to EE and the results are graphically represented below:

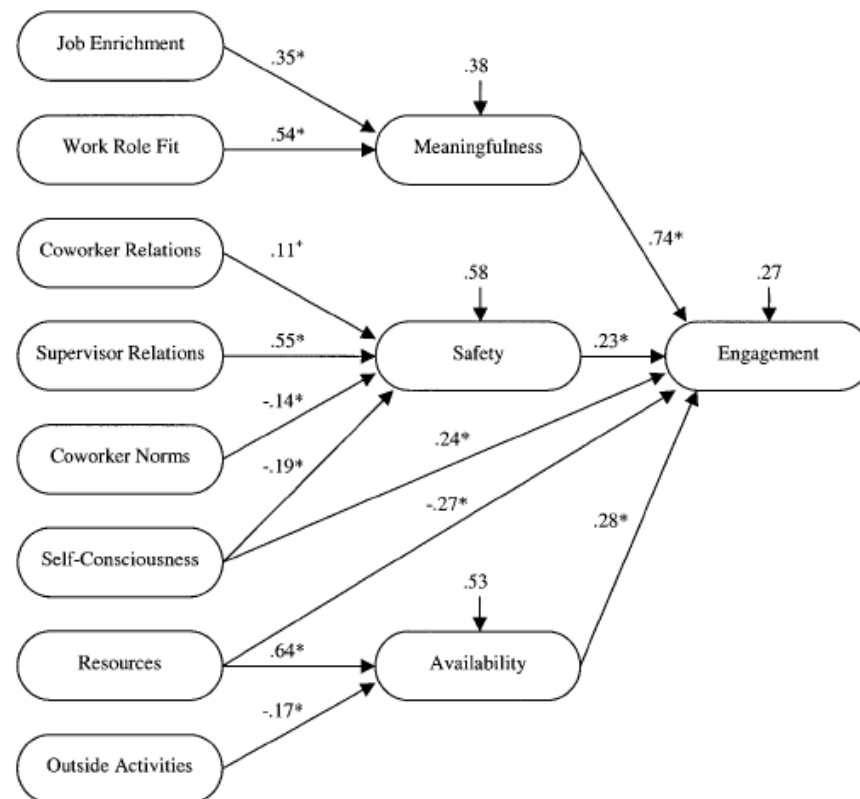


Figure 3: Dimensions of employee engagement

Adapted from: "The psychological conditions of meaningfulness, safety and availability and the engagement of the human spirit at work," by May et al., 2011, *Journal of Occupational and Organizational Psychology*, 77(1), p. 28. Copyright 2011 by The British Psychological Society.

The study provided evidence that all 3 psychological dimensions, as per Figure 3 above, displayed significant positive relationships with EE however, meaningfulness proved to be its strongest predictor and fully explained why enriching jobs and high levels of fit result in EE (May et al., 2004).

The organisational outcomes of DE and ITT were established in literature by Saks (2006) followed by Shuck et al. (2011) when the 3 psychological dimensions were extended to an antecedent and outcome model and was used to measure EE. The model suggested that job fit, affective commitment and psychological climate enables EE, the outcomes of which can be measured by DE and ITT (Shuck et al., 2011). Results of the study reported a relationship between the enablers and EE and that EE exhibited a significant: (1) positive relationship with DE and (2) negative relationship with ITT (Shuck et al., 2011).

To the contrary on the above, *meaningless* work results in demotivation, detachment from one's work, loss of morale and a degree of cognitive dissonance (May et al., 2004) and may be perceived as manipulation by the employer, potentially leading to sub-optimal work outcomes (Bailey et al., 2017). Employees, who have rewarding, and enriching jobs may experience meaninglessness if their organisations try to emotionally manage work meaningfulness such as influencing employees to subscribe to an organisational value system that they don't align to or drive excessive working hours to tout work meaningfulness when the true intention is a profit motive. Bailey et al. (2017) suggest that "existential labour" (p. 18), a phenomenon of unconcealed or deliberate adoption of attitudes and behaviours in response to an attempt to emotionally manage work meaningfulness, is a situation where an employee is inauthentic in self-agency and experiences misalignment between organisational and personal value systems.

Given RPA's ability to impact the meaningfulness domains of work tasks, roles and interactions (Bailey et al., 2017) that is evident in the above literature (Asatiani & Penttinen, 2016; Autor, 2015; Avasthy, 2019, Davenport, 2011; Davenport & Kirby, 2016; Lacity & Willcocks, 2015; Lacity & Willcocks, 2016; Lacity et al., 2015; Lhuer, 2016; Mendling et al., 2018; Oldham & Fried, 2016; Willcocks et al., 2015; Willcocks et al., 2017) and its ability to rationalise the sensemaking process (Aguinis & Glavas, 2019), it can be hypothesised that RPA will correlate positively with meaningfulness:

Hypothesis 1: RPA has a positive relationship with meaningfulness

Furthermore, the importance of meaningfulness within work and its impact on effort levels and staff attrition is evident in the above literature. In addition, meaningfulness being the largest contributor to EE (May et al., 2014) and given EE's relationship with these outcomes (Saks, 2006; Shuck et al., 2011), predicting DE (Shuck et al., 2011) and influencing ITT (Allen et al., 2010), it can be hypothesised that meaningfulness will correlate positively with DE and negatively with ITT:

Hypothesis 2: Meaningfulness has a positive relationship with DE

Hypothesis 3: Meaningfulness has a negative relationship with ITT

2.4 Discretionary effort

Effort is defined as a type of arousal but manifests differently. Unlike traditional types of arousals such as those originating from music or eating something satisfying, the exertion of effort is as a result of one focusing on an activity, rather than what is being acted out upon them (Kahneman, 1973). DE is defined as the exerted effort that exceeds the agreed upon minimum as contractually agreed between employer and employee (Frenkel & Bednell, 2016). Therefore, the quantum of extra effort is a function of one's discretion and hence is behaviour of a voluntary nature.

Behaviours can be classified as in-role when required for the execution of contractually agreed upon tasks (Vey & Campbell, 2004) or extra-role when it's not a contractual prerequisite for one's job but creates a harmonious environment for the fluid functioning of the organisation (Lee & Allen, 2002). Organisational Citizenship Behaviour (OCB) is an example of an extra-role behaviour (Bolino, Hsiung, Harvey, & LePine, 2015) which is largely discretionary and may be directed towards the assistance of an employee or towards the organisation to indirectly assist it with achieving its goals (Saks, 2006). It enhances social capital and creates a psychologically conducive work environment but is not generally associated with organisational rewards (Bolino et al., 2015). DE is considered a task-related form of OCB (Frenkel & Bednell, 2016) however research has provided evidence that DE and OCB are separate (Lloyd, 2008).

DE however may be associated with organisational rewards, but its psychological manifestation makes it difficult to measure and quantify (Kahneman, 1973) however, the *result* of such effort in the form of high performance provides a basis for tangibility and subsequent quantification (Lloyd, 2008). Effort and performance have always been associated with each other and DE forms part of the performance domain and has a direct relationship with organisational performance (Brown & Leigh, 1996; Lloyd, 2008). It was predicted by the possession of requisite skills for doing a job and autonomy with autonomy exhibiting a stronger relationship than skills (Lloyd, 2008) as it allowed employees a degree of freedom to do their jobs. Furthermore, knowledge workers cite autonomy as an important attribute that enables the effective and efficient completion of their work (Gambardella et al., 2015).

DE is one of the outcomes of EE (Macey & Schneider, 2008; Saks, 2006; Shuck et al., 2011; Shuck & Wollard, 2010) and engaged employees exert 57% more effort

than usual (Buchanan, 2004). The antecedent and outcome model of EE (Shuck et al., 2011) reported that DE was predicted by the following constructs when subjected to a hierarchical regression analysis: (1) supportive management, (2) contribution and (3) challenge. The reported findings contradicted the initial hypothesis that EE will predict variances in DE (Shuck et al., 2011). Supportive management, contribution and challenge were dimensions of the reported antecedent to EE – psychological climate (Brown & Leigh, 1996) which describes the working environment created by management for an employee to succeed.

A closer inspection of the psychological climate measurement scale, that was developed Brown and Leigh, (1996), that was used in Shuck's et al., (2011) study is required to understand this prediction (please refer to Appendix A for complete scale). Supportive management describes the overall flexibility demonstrated by management, including a degree of latitude in decision making and non-prejudicial treatment, to the employee in the execution of their jobs (Brown & Leigh, 1996). Analysis of the subscale provided evidence of high degrees of autonomy, for example: *"My boss gives me the authority to do my job as I see fit"* and *"My boss is flexible about how I accomplish my job objectives"* (Shuck et al., 2011, p. 144). Contribution describes the employees' perceived value of the work they do to the attainment of organisational goals (Brown & Leigh, 1996). The subscale suggests in part the importance of skill utilisation in task execution and how this contributes to organisational success, for example *"I feel very useful in my job"* (p. 144) and *"The work I do is very valuable to the organization"* (p. 145). Lastly, challenge refers to the extent to which a job exploits an employees' capabilities (Brown & Leigh, 1996) and is a function of how well a job is designed (Kahn, 1990; May et al., 2004). The subscale provides evidence of how job characteristics are important to work output, for example, *"My job is very challenging"* and *"It takes all my resources to complete my work objectives"* (p. 145).

The analysis above of DE in this study (Shuck et al., 2011) resonates with earlier studies of autonomy and skill variety beings the drivers of DE (Lloyd, 2008). Furthermore, it can be argued that given the task-altering nature of RPA, where routine tasks are automated and existing work is restructured to allow employees to focus on abstract tasks (Asatiani & Penttinen, 2016; Autor, 2015; Avasthy, 2019, Davenport, 2011; Davenport & Kirby, 2016; Lacity & Willcocks, 2015; Lacity & Willcocks, 2016; Lacity et al., 2015; Lhuer, 2016; Mendling et al., 2018; Oldham &

Fried, 2016; Willcocks et al., 2015; Willcocks et al., 2017), work will become more challenging and skill utilisation will be optimised. Autonomy may also be improved since data that may be required by knowledge workers for on-the-job decision making will be readily available as a result of RPA. As such, it can be hypothesised that RPA will positively correlate with DE:

Hypothesis 4: RPA has a positive relationship with DE

Given the voluntary nature of DE, an impetus may be required to achieve the outcome of greater effort (Lloyd, 2008) and this rationale can be demonstrated by the relationship between job enrichment and EE (May et al., 2004). The study found that an enriching job does not necessarily equate to high levels of engagement since work, as a result of job enrichment, had to be meaningful for engagement to exist (May et al., 2004). Therefore, when exposed to a stimulus in the form of RPA, a decision will be made by an employee as to whether greater effort levels should be exerted. This decision will be guided by whether the task-altering and work-restructuring nature of RPA makes work more significant (Rosso et al., 2010) and enriching and positive (Bailey et al., 2017), as per the researcher's operational definition of meaningfulness. Thereafter, using the process of sensemaking (Aguis & Glavas, 2019) meaningfulness will be established and the decision to exert greater effort levels is acted upon. In sum, it can be hypothesised that meaningfulness will explain why a relationship between RPA and DE exists:

Hypothesis 6: Meaningfulness will mediate the relationship between RPA and DE

2.5 Intention to turnover

Employee turnover describes the entry and exit of employees into and out of an organisation and is measured by an employees' duration of employment and how often they need to be replaced (Woods, 2013). Turnover may be a choice by the employee and as such, voluntary or it may be imposed on to the employee by the organisation for reasons such as poor performance, economic downturn or

organisational restructuring initiatives (Allen et al., 2010). For the purposes of this research, only voluntary turnover will be examined. ITT is described as an employees' voluntary departure from the organisation (Saks, 2006). Voluntary leavers are generally the high performers (Allen et al., 2010) therefore, retention strategies that are typically focussed towards voluntary turnover are focussed on creating conducive work climates and rewards (Vandenberghe, Bentein, & Panaccio, 2017).

2.5.1 The cost of staff turnover

Staff turnover is costly to an organisation (Allen et al., 2010) and studies prove that turnover is negatively related to financial performance because of increasing costs associated with rehiring and re-establishing workforce equilibrium (Park & Shaw, 2013; Trevor & Nyberg, 2008). Rehiring costs are incurred immediately and are referred to as replacement costs (Allen et al., 2011) and consists of costs relating to recruitment, selection and training and ranges between 90% and 200% of annual salary.

Separation costs are made up of *tangible* and *intangible* costs. The tangible costs are quantitative in nature and may relate to any accrued leave that was owing to the employee or costs relating to temporary staff or overtime paid to existing staff in the absence of the employee. The intangible costs are qualitative in nature and has an indirect impact on organisational sustainability through loss of institutional memory, diversity and team disruptions (Allen et al., 2010). Given its eroding nature to the organisational fabric, intangible costs may prove to have greater negative long-term impact on the organisation than the direct impact of short-term cost incurrence.

2.5.2 Predictors of staff turnover

A myriad of reasons influences an employee's decision to turnover. Early research found that inability to identify with a job and a lack of significance were negatively related to ITT (Hackman & Oldham, 1976) together with psychologically aligning with one's job (Blau & Boal, 1987). Subsequent research suggested that unmet salary and promotional expectations are primarily why employees may voluntarily leave the

organisation (Houkes, Janssen, Jonge, & Nijhuis, 2001), a finding that was subsequently refuted, proving that job satisfaction and salary were insignificant to turnover intention (Allen et al., 2010). Job embeddedness, which describes an employee's links to others, organisational fit and opportunity cost of leaving as a key predictor (Mitchell, Holtom, Lee, Sablinski, & Erez, 2001) while organisational downsizing was reported to impact employees' voluntary turnover decision irrespective of whether they were affected by the downsizing or not (Trevor & Nyberg, 2008).

A meta-analysis of numerous studies outlining why staff would turnover (Allen et al., 2010) suggested that the withdrawal process, which describes the process of an employee psychologically disconnecting from one's job, considering alternative employment and commencing with job searching activities, as the largest predictor of ITT. From the perspective of the researcher, the shortcoming of this as approach is that it fails to uncover the root-cause of an employee psychologically disconnecting from their job. The myriad of reasons provided above from previous research provides insight as to why an employee may psychologically disconnect from one's job and as Allen et al. (2010) suggests, this process should originate from an evaluation of one's job. Well-designed jobs that contribute to autonomy, skill variety and meaningfulness are associated with a reduced ITT (Allen et al., 2010; Hackman & Oldham, 1976, Saks, 2006) and role clarity proved to be the strongest predictor of ITT from a job characteristics perspective (Allen, et al., 2010).

Furthermore, ITT is one of the outcomes that is negatively related to EE (Harter et al., 2002; Macey & Schneider, 2008; Saks, 2006; Schaufeli & Bakker, 2004; Shuck et al., 2011; Shuck & Wollard, 2010) since engaged employees are reported have an 87% less of an intention to turnover (Buchanan, 2004). The antecedent and outcome model of EE (Shuck et al., 2011) reported that ITT was predicted by the following constructs when subjected to a hierarchical regression analysis: (1) affective commitment, (2) meaningfulness and (3) availability.

Affective commitment, one of the reported enablers to EE in this study describes the emotional bond that an employee has with their organisation (Rhoades, Eisenberger, & Armeli, 2001) together with the EE dimensions of meaningfulness and availability (Kahn, 1990) predicted negative variance in ITT (Shuck et al., 2011). Availability refers to the extent by which (1) physical resources are made available by the organisation and (2) the employee has the psychological wherewithal to commit

resources to the completion of work (Kahn, 1990; May et al., 2004). Furthermore, the meaningfulness prediction in this study supports hypothesis H2 proposed in Section 2.3.3.

Given RPA's task altering principles, the probability of well-designed work that's autonomous and effective in utilising one's skill is high within the context of an RPA agenda (Asatiani & Penttinen, 2016; Autor, 2015; Avasthy, 2019, Davenport, 2011; Davenport & Kirby, 2016; Lacity & Willcocks, 2015; Lacity & Willcocks, 2016; Lacity et al., 2015; Lhuer, 2016; Mendling et al., 2018; Oldham & Fried, 2016; Willcocks et al., 2015; Willcocks et al., 2017). Furthermore, RPA will contribute to providing resources to effectively complete and restructure work to improve one's self-image and perception of the job (Bailey et al., 2017; Kahn, 1990). Given the predictors of ITT described above (Allen et al., 2010; Bailey et al., 2017; Kahn, 1990; Shuck et al., 2011), it can be hypothesised that RPA will correlate negatively with ITT:

Hypothesis 5: RPA has a negative relationship with ITT

As a point of departure, the name "*intention to turnover*" that was assigned to the construct needs examination as it consists of two distinct but related elements that are often used collectively (Hom, Mitchell, Lee, & Griffeth, 2012). The voluntary turnover model (Allen et al., 2010) articulated that the *intent*, which is essentially the decision point of wanting to turnover is the largest predictor of the *turnover* event and this intent is formed after an evaluation of the current job. However, the intent and turnover event should be separated because any intervention that may exist between the intent and action will be considered and will subsequently guide the voluntary decision of whether one should turnover or not (Hom et al., 2012). Thus, within the context of RPA, an employee will evaluate his or her job and form an intention based on this evaluation. The decision as to whether that employee remains in the organisation or not will be determined by the extent to which meaningfulness can be derived from the job via a sensemaking process (Aguinis & Glavas, 2019). It can therefore be hypothesised that meaningfulness will explain the negative relationship that may exist between RPA and ITT:

Hypothesis 7: Meaningfulness will mediate the relationship between RPA and ITT

2.6 Proposed theoretical model and conclusion

The purpose of this research was to understand how an emerging technology in the form of RPA, influenced voluntary work outcomes of DE and ITT, that are strongly associated with organisational performance, of knowledge workers. Based on the above literature review research hypotheses were systematically derived and the following theoretical model is put forward by the researcher:

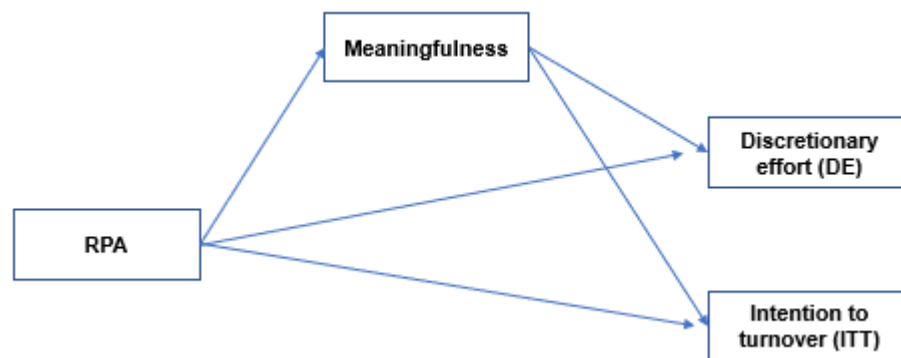


Figure 4: Proposed theoretical framework with relationships

Statistically, the model seeks to empirically test the mediating effect of meaningfulness on the relationship between RPA and outcome variables of DE and turnover intention. The research hypotheses that have been derived from the literature will be used to test the proposed research model. For mediation to be tested and proven, significant causal pathways must exist between all constructs (Baron & Kenny, 1986; Preacher & Hayes, 2004). As a result, relationships that may have been proven in previous studies (H_1 : meaningfulness has a positive relationship with DE and H_2 : meaningfulness has a negative relationship with ITT) must be proven again within this study for the purposes of mediation. The proposed mediation tests depicted in Figure 4 above between RPA and DE and ITT will be performed separately via individual mediation models. For the purposes of demonstrating the proposed theoretical model, the mediated relationships are being shown together.

CHAPTER 3: RESEARCH HYPOTHESES

3.1 Introduction

The purpose of this research was to understand how an emerging technology in the form of RPA, influenced voluntary work outcomes of DE and ITT, that are strongly associated with organisational performance, of knowledge workers. Based on the literature reviewed in Chapter 2 of this research, the following theoretical model has been developed and research hypotheses have been systematically derived. Each path in this model represents a research hypothesis that will be tested to empirically prove this proposed model.

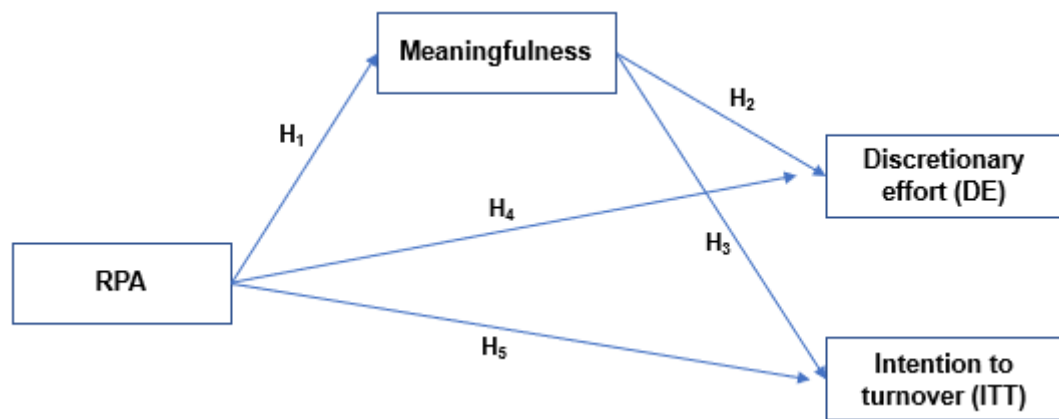


Figure 5: Proposed theoretical framework with hypothesised paths

3.2 Research hypotheses

H₁: There is a positive relationship between RPA and meaningfulness.

H₂: There is a positive relationship between meaningfulness and DE.

H₃: There is a negative relationship between meaningfulness and ITT.

H₄: There is a positive relationship between RPA and DE.

H₅: There is a negative relationship between RPA and ITT.

H₆: Meaningfulness mediates the relationship between RPA and DE.

H₇: Meaningfulness mediates the relationship between RPA and ITT.

CHAPTER 4: RESEARCH METHODOLOGY AND DESIGN

4.1 Introduction

The purpose of this research was to understand how an emerging technology in the form of RPA, influenced voluntary work outcomes of DE and ITT, that are strongly associated with organisational performance, of knowledge workers. The following chapter outlines the method that was adopted in order to effectively test the research hypotheses that was derived from the literature reviewed in Chapter 2 and consolidated in Chapter 3. Furthermore, given the academic infancy of RPA, an effective measurement scale had to be developed, using a system process of scale development, so that data could be collected, analysed and interpreted in order to understand RPA's effect on the constructs of meaningfulness, DE and ITT (Williams, 2007).

4.2 Research design

Creswell (2003) described positivism as a research philosophy that subscribed to a scientific research method where the researcher sought to understand what may have caused determined effects or outcomes. A positivist philosophy is underpinned by the law of cause and effect (Creswell, 2003; Saunders & Lewis, 2012) together with scientific and quantitative methods. The researcher sought to understand how an emerging technology in the form of RPA, influenced voluntary work outcomes of DE and ITT, that are strongly associated with organisational performance, of knowledge workers. Therefore, a positivist philosophy governed by the law of cause and effect was adopted for the purposes of this study. Furthermore, the analytical mind of the researcher was aligned to the scientific and statistical philosophy of positivism.

In addition to the analytical alignment, the researcher is experienced in business process reengineering, RPA and change management. The researcher has worked for multinational organisations across global business contexts and was responsible for the optimisation of business processes, either through process re-design and standardisation or RPA implementation. From a practical and employee perspective,

the key outcomes of business process re-engineering and RPA is increased levels of effectiveness and efficiency through either task re-design or improved skill utilisation. The researcher therefore had practical understanding and experience of how RPA influenced tasks within jobs, effort levels and, to an extent, employee turnover. The alignment between the researcher's practical experience and this study allowed for a pragmatic conceptualisation of the principles that underpinned RPA within the context of this study and empirically test it.

A positivist philosophy uses research hypotheses test relationships between RPA, meaningfulness, DE and ITT, values objectivity in research processes and assumes that observable data is reliable (Gemma, 2018; Saunders, Lewis, & Thornhill, 2009; Straub, Boudreau, & Gefen, 2004). Given that the researchers own philosophy was based on scientific and analytical underpinnings, there was a state of congruence between the research and the researchers own philosophy thus suggesting lower levels of bias (Holden, 2004; Saunders et al., 2009).

A quantitative research methodology utilises specific statistical techniques or methods to collect, analyse and interpret data for a study thereafter producing a written narrative to describe and interpret the results (Creswell, 2003). Furthermore, a quantitative methodology is "specific in its surveying or experimentation, as it builds upon existing theories" (Williams, 2007, p. 66). A quantitative methodology was therefore adopted since statistical techniques were used to test the hypotheses that were derived from a review of literature in Chapter 2 to understand the relationship between RPA and the outcome variables of DE and ITT.

A deductive approach was used when analysing the relationship between RPA and the outcome variables of DE and ITT. In the process of explaining the cause and effect relationship between these variables, the researcher relied on theory that was based on what was already known to be true, collected data in a quantitative format and applied statistical control procedures to ensure that the data was valid (Saunders et al., 2009; Zikmund, Babin, Carr, & Griffin, 2012) regarding meaningfulness, the outcome variables and RPA. Apart from a deductive approach being more suited to quantitative research methods (Trochim & Donnelly, 2006), it is also used when trying to explain causal relationships between variables (Saunders et al., 2009).

A study that subscribes to an explanatory design is driven by theory and seeks to explain relationships between independent and dependent variables (May et al.,

2004; Saks, 2006; Saunders et al., 2009; Shuck et al., 2010). This research sought to understand how an emerging technology in the form of RPA, influenced voluntary work outcomes of DE and ITT, that are strongly associated with organisational performance, of knowledge workers and to explain what that relationship effectively meant (De Vaus & de Vaus, 2001). In the context of this study, the potential relationship between the **dependent variable** (RPA) and **independent variables** (DE and ITT) is being explained or **mediated** by meaningfulness as per the following proposed model:

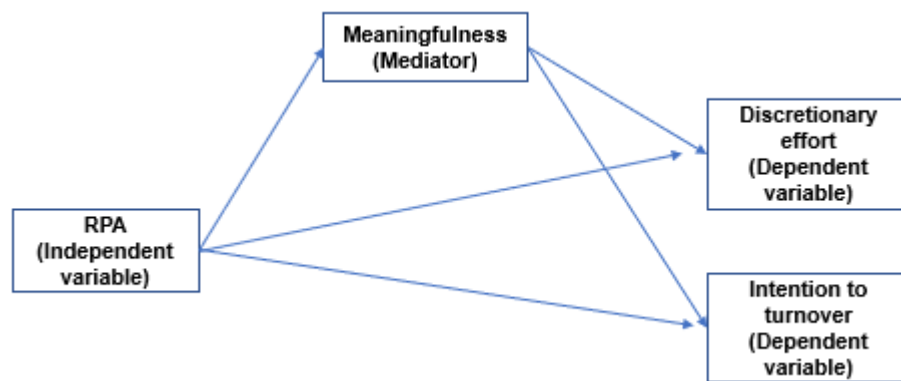


Figure 6: Proposed relationship between dependent, mediator and independent variables

Since the research hypothesis that were outlined in Chapter 3 to test and explain the relationship between the dependent and independent variables were derived from theoretical frameworks in Chapter 2. Therefore, an explanatory research design was adopted in line with other research that tested relationships between independent and dependent variables according to similar explanatory principles (May et al., 2004; Saks, 2006; Shuck et al., 2010).

Manual or online surveys proved to be a popular method for data collection (May et al., 2004, Rich et al., 2010; Saks, 2006; Schaufeli & Bakker, 2004; Shuck et al., 2010). For the purposes of this research, a structured online survey was employed as a measurement instrument that was administered only once according to a cross-sectional time horizon. The single measurement instrument aligned to a mono-method choice due to cost and time constraints. The structured online survey, which was guided by the literature review and research questions, supported the quantitative design that was proposed since the purpose of this research was to quantify the relationship between variables (the mediating effect of meaningfulness on the relationship between RPA and the outcome variables of DE and ITT). The

structured online survey that was administered was a convenient and cost-effective method to collect data in order to test the research hypotheses together with enabling efficient analysis of the results using statistical methods in line with quantitative data collection techniques. Please refer to Section 4.6 where the measurement instrument is discussed in greater detail.

4.3 Population

Research population is defined as, “Any complete group of entities that share some common set of characteristics” (Zikmund et al., 2012, p. 682) and may include organisations, places or people (Saunders & Lewis, 2012). The population for this study consisted of knowledge workers who have tasks within their jobs impacted by RPA via digital task automation, being the common characteristic, across various sectors in an economy (not limited to South Africa). Furthermore, workers performing physical tasks that are impacted by physical task automation will not form part of the population since these workers are considered manual workers and not knowledge workers.

A clear distinction exists between robots that perform physical tasks and those that perform digital tasks and both physical and digital task automation are a subset of **repetitive task automation** (Davenport & Kirby, 2016), an automated, rules-based decision-making process that relies on an algorithm. Physical task automation refers to a mechanical robot, controlled by a computer, that performs physical tasks that were previously performed by a human, for example, a robot that performs welding on automobile chassis on a production line that was previously welded by a human. Digital task automation refers to the automation of administrative tasks and decisions where a robot can navigate through a business process and make basic decisions based on simple business rules and logic.

4.4 Unit of analysis

The unit of analysis for a research study “indicates what or who should provide the data and at what level of aggregation” (Zikmund et al., 2012, p. 146) to which the researcher can make generalisations. For the purposes of this study, the researcher

sought to understand how an emerging technology in the form of RPA, influenced voluntary work outcomes of DE and ITT, that are strongly associated with organisational performance, of knowledge workers. Therefore the unit of analysis for the purposes of this study was defined as knowledge workers that have tasks within their jobs impacted by RPA.

4.5 Sampling method and size

Probability sampling is a technique where every single member of the population has an equal chance of being selected. Non-probability sampling is a technique where the researcher uses judgement or convenience to select a sample from the population (Creswell, 2003; Zikmund et al., 2012). For the purposes of this study, and given that knowledge workers both locally and internationally constitutes the complete population, the researcher adopted a non-probability sampling technique that identified suitable respondents that matched the sample criteria of knowledge workers and exposure of tasks within their jobs to RPA.

The survey was distributed to all the knowledge workers in the researcher's network via social media platforms such as LinkedIn and WhatsApp together with email. Due to the researcher's knowledge on the topic of research, generalisations were made regarding the characteristics of respondents that the survey will be sent to and this is an example of judgement sampling (Saunders & Lewis, 2012). The survey was then distributed according to snowballing technique through the selected individuals in the researcher's network based on the researcher's assessment of the participants' work and their exposure to RPA.

The researcher proposed a sample size that will be based on the minimum required to test the power of significance for the proposed statistical technique of a mediated regression analysis (Green, 1991; VanVoorhis & Morgan, 2007). The sample size was calculated based on $50 + 8k$ whereby k represents the number of predictors in the research model. This target number was calculated as a sample size of 90. The researcher endeavoured to ensure this was met and sought a minimum sample size of 200 respondents.

4.6 Measurement instrument

As discussed in Chapter 4.2 above, the researcher adopted a positivist philosophy and deductive research approach that guided a quantitative methodology in the collection, analysis and interpretation of data. The structured online survey that was administered was a convenient and cost-effective measurement instrument that was used to gather information relating to the research hypotheses and enabled efficient analysis of the results using statistical methods that were in line with quantitative data collection techniques.

4.6.1 Structured online survey

The measurement instrument was a structured online survey that was administered only once according to a cross-sectional time horizon and the single data collection tool aligned to a mono-method choice due to cost and time constraints. The questions in the survey, that were guided by the literature review and research hypotheses, supported the quantitative design that was proposed since the purpose of this research was to quantify the relationship between variables (the mediating effect of meaningfulness on the relationship between RPA and the outcome variables of DE and ITT).

A Likert scale was used to quantify the responses in line with quantitative research techniques and Hinkin (1998) suggests that the scale should be appropriately calibrated so that the appropriate level of variation can be captured. When responding to an item, a typical Likert scale allows respondents to choose one of 5 categories (5-point scale) with 1 denoting strongly disagree and 5 denoting strongly agree (Jamieson, 2004; Hinkin, 1998).

Cohen, Manion and Morrison (2007) suggested that a 5-point scale may not offer much choice should respondents choose to ignore the polar end points (strongly agree or disagree) of a 5-point scale and proposed that a 7-point scale may provide a wider spectrum of response options to choose from even though the alpha coefficient for reliability shows no increase with scales greater than five calibration points (Hinkin, 1998). However, for the purposes of this research, a 7-point Likert scale was adopted for all responses relating to the first order measurement scales of

RPA, meaningfulness, DE and ITT in order to cater for the variation that may exist in responses (Cohen et al., 2007) where 1 represented strongly agree and 7 represented strongly disagree.

A sample of the questionnaire is provided in Appendix A and has been structured in the following manner:

1. A preamble section that introduced the researcher, the purpose of the study, a brief description of what RPA is and how it works, the estimated completion time of the survey together with the anonymity and confidentiality assertions undertaken by the researcher.
2. Part A: Demographic data including a screening question regarding RPA's impact on tasks within the respondents' job, educational qualifications, job level, age group, tenure and job description.
3. Part B: Questions 8 – 13 related to the construct of meaningfulness.
4. Part C: Questions 34 – 40 related to the construct of DE.
5. Part D: Questions 41 – 43 related to the construct of ITT.
6. Part E: Questions 44 – 52 related to the construct of RPA (4 questions were subsequently removed, refer to Section 6.4 for further detail).

The break in sequence between Part B and Part C is due to a scope revision of this study. Initially, RPA's impact on DE and ITT was initially conceptualised with affective commitment, psychological climate and meaningfulness, and as such, data was collected for all the mentioned constructs. It was subsequently decided to further refine the scope of the study after the data collection phase to only include meaningfulness in the analysis between RPA, DE and ITT. This was done to further refine the scope of this study and focus it on as few constructs as possible to preserve the simplicity of the proposed mediation model.

Measurement scales in this questionnaire were either adapted from existing literature due to the researcher's inexperience (Saunders & Lewis, 2012) or developed by the researcher in accordance with scale development techniques that was based on principles from existing literature together with the researcher's practical experience. Due to lack of academic literature regarding RPA, the measurement scale for RPA was developed by the researcher to test the construct within this study and the relevant procedures and statistical tests in accordance with scale development techniques (Carpenter, 2018; Churchill, 1979; Hinkin, 1995; Reidenbach & Robin,

1990; Tay & Jebb, 2016; Worthington & Whittaker, 2016) were abided by as far as possible to ensure that the scale conformed to acceptable levels of validity and reliability. Refer to Section 4.6 for further detail.

Part A: Demographic data

The questions in this section provided insights into the respondents' age (within predefined ranges), job level, education level, length of service (within predefined ranges) and industry. A screening question of '*are tasks within your job impacted by RPA?*' was posed at this point. In the preamble section, the concept of RPA was explained and contextualised within the ambit of work so that respondents were aware of what the acronym meant and what it sought to achieve within the survey. This screening question was used as the first segmentation point of the data upon analysis.

The last question within this demographics section, that required the respondent to best describe their current daily work, was adapted from Davenport (2011) and is based on the structured provision of knowledge model. As per the detailed discussion of this model in Section 2.2.2, its purpose was to understand what type of knowledge work knowledge workers are performing [(1) repeatable work, (2) improvisational work, (3) routine work (4) judgement-oriented work] since different kinds of knowledge work require different support technologies (Davenport, 2011). There are 8 adapted alternatives to this question and the respondent was required to choose a maximum of 2 responses. The purpose of this question was to segment the work categories into easily automatable and not easily automatable and create a nomenclature for routine and abstract tasks that will be used throughout the study. Feedback from this question also provided insights into the suitability of the job for automation and how this impacted the relationships between RPA, meaningfulness, effort and turnover.

Part B: Meaningfulness

The questions for the first order construct of meaningfulness was adapted in its entirety from the studies of EE by May et al. (2004) to understand how the

psychological dimensions of EE (Kahn, 1990) contributed to its measurement. A total of 6 items on this scale quantified the level of meaning that respondents derived from their daily work activities using a 5-point Likert scale. With an alpha coefficient of 0.90 ($\alpha = 0.90$), this represented a measurement scale with a high degree of internal consistency (Zikmund et al., 2012). The meaningfulness subscale by May et al. (2004) was used in the Shuck et al. (2011) study of antecedent and outcome variables as a dimension, together with availability and safety, for measuring the EE construct.

Part C: Discretionary effort

For the first order construct of DE, questions were adapted from the studies performed by Lloyd (2008) to understand whether skills and autonomy predicted DE levels and how DE differed from other organisational performance behaviours. A total of 7 items measured employees' DE levels using a 5-point Likert scale. With an alpha coefficient of 0.87 ($\alpha = 0.87$), this represented a measurement scale with a high degree of internal consistency (Zikmund et al., 2012). The DE scale by Lloyd (2008) was used in the Shuck et al. (2011) study of antecedent and outcome variables as an outcome variable with a positive relationship to EE.

Part D: Intention to turnover

The questions for the first order construct of ITT was adapted from the studies by Colarelli (1984) of realistic job previews to understand how different methods of communicating job descriptions to new employees influenced their intention to quit. A total of 3 items measured respondents' ITT using a 5-point Likert scale. This measurement scale yielded an alpha coefficient of 0.75 ($\alpha = 0.75$) and was representative of a scale with a high degree of internal consistency (Zikmund et al., 2012). The ITT scale by Colarelli (1984) was used in the Shuck et al. (2011) study of antecedent and outcome variables as an outcome variable with a negative relationship to EE.

Part E: RPA and scale development

RPA is a relatively new phenomenon that is still in its infancy stages with organisations only recently showing an increase in adoption rates (Agaton & Swedberg, 2018; Willcocks et al., 2015) and due to its relative newness, there was a limited amount of academic literature regarding the construct. The purpose of this research was to understand how an emerging technology in the form of RPA, influenced voluntary work outcomes of DE and ITT, that are strongly associated with organisational performance, of knowledge workers. Statistically, this involved performing a mediated regression analysis. Academic literature regarding meaningfulness, DE and ITT were abundant from studies on EE. Therefore, measurement scales were adapted from existing academic literature in order to quantify these constructs for the purposes of this study.

In order to measure the construct of RPA, a scale had to be developed consisting of items that were a reliable and valid representation of the construct within the context of this study (Carpenter, 2018; Churchill, 1979; Hinkin, 1995; Reidenbach & Robin, 1990; Tay & Jebb, 2016; Worthington & Whittaker, 2016). Hinkin (1995) reviewed the procedures, best practices and common problems encountered during the scale development process of 277 measurement scales that were developed and used for evaluating constructs in 75 articles published in reputable academic journals. Numerous findings, principles and recommendations from Hinkin's (1995) extensive scale development review was considered and contributed to the development of the RPA scale used in this study.

Approaches to scale development followed the similar principle to the development of an overall research approach (Saunders & Lewis, 2012; Tay & Jebb, 2016). The approach followed can either be a deductive approach based on existing theory, knowledge and conceptualisations will drive the item generation for the construct or an inductive approach where the construct was not easily conceptualised or defined, and item generation is guided by experts in the relevant area of specialisation (Hinkin, 1995; Tay & Jebb, 2016; Worthington & Whittaker, 2016).

Scale development is an onerous process, the success of which is a function of how accurately and reliably the scale can capture the true essence of the construct (Hinkin, 1995). Worthington and Whittaker (2016) outlined three strategies for scale development: logical, theoretical and empirical. The logical development strategy is

solely reliant on the scale developer's understanding and sometimes practical knowledge of the construct in order to generate the scale items whereas the theoretical strategy solely relies theory for item generation. Both the logical and theoretical strategies are no longer preferred approaches to scale development since a lack of statistical rigour and high degrees of subjectivity compromises the reliability and validity attributes of the scale. The empirical approach employs statistical techniques to ensure that the scale was valid and reliable and that items are grouped appropriately.

A succinct understanding of the concepts of reliability and validity within the context of scale development, together with examining the relationship between these concepts, were required. In the context of this study, the researcher sought to empirically test the mediating effect of meaningfulness on the relationship between RPA and the outcome variables of DE and ITT of knowledge workers. Therefore, the measurement scale for the RPA construct was defined as **the degree to which tasks within a job are impacted by RPA** (refer to Section 2.2.2 for further detail). The differences in measurement scores of the RPA construct from respondents will not only be reflective of the theoretical underpinnings of RPA, which can be referred to as *true differences* (Churchill, 1979) but will also be reflective of a *measurement error* which is constituted of a *random error* and *systematic error* (Bagozzi & Phillips, 1991). A random error may be due to differences in scores as a result of a respondent's mood or tiredness and a systematic error may be due to differences in scores as a result of a respondent's prejudices, biases or actual willingness to truthfully answer questions (Bagozzi & Phillips, 1991; Churchill, 1979).

Therefore, the RPA measurement scale, within the context of this study, was said to be **valid** when differences that arose from respondents were as a result of the theoretical concept of RPA or *true differences* and not random or systematic errors. The scale was said to be **reliable** if the measurement scale produced consistent results in independent tests (Churchill, 1979). The relationship between validity and reliability is unique. Since reliability depends on the level of random errors where perfect reliability means that there are no random errors, should the RPA scale prove to be valid, then reliability would have been proved also. However, the RPA scale being reliable did not secure its validity, as differences in measurements could have been attributable to systematic errors or true differences (Churchill, 1979; Hair et al., 2010).

Therefore, validity together with reliability is important when assessing the statistical viability of a scale and a scale should demonstrate validity from 3 perspectives – content, criterion and construct together with internal consistency for reliability (Hinkin, 1995). From a validity perspective within the context of this study, content validity assessed how well the items within the scale *captured* the extent to which RPA aligned to its proposed definition, criterion validity assessed the extent to which the scale was *related* to the outcome of what the RPA construct set out to measure and construct validity assessed how well the items within the scale actually *measured* RPA in terms of its definition. From a reliability perspective, if items within the RPA measurement scale are homogenous, then the scale is said to be internally consistent (Clark & Watson, 1995; Hinkin, 1995). Various statistical techniques were used to assess the validity and reliability of the RPA measurement scale that was developed. This will be discussed further below and in greater detail in Section 4.8 of this study.

Carpenter (2018), Churchill (1979), Clark and Watson (1995), Hinkin (1995), Reidenbach and Robin (1990), Tay and Jebb (2016) and Worthington and Whittaker (2016) have all proposed techniques for scale development that begin with conceptualising the construct from a logical perspective, employing theoretical frameworks and expert consultation for item generation and empirically testing the scale for validity and reliability using statistical techniques during the process to refine it. Carpenter (2018) provided the most contemporary research regarding scale development and suggested a 10-step approach that was similar in structure to Churchill (1979). For the purposes of this study, the 8-step scale development framework that was formulated by Churchill (1979) was used as the basis for the development of the RPA scale due to its extensive use by other scholars and it holistically encompassed the attributes of all the other proposed approaches. However numerous suggestions and substantiations asserted by Carpenter's (2018) research guided the RPA scale development process in this study.

Scale development steps

Step 1 Specify the domain: The researcher was able to delineate the concept of RPA by referring to literature by Autor (2015), Autor and Price (2013), Avasthy (2019), Davenport and Kirby (2016), Lacity et al. (2015), Lacity and Willcocks (2016),

Lhuer (2016), Mendling et al. (2018) and Willcocks et al. (2015) and proposed the following operational definition for RPA: *Robotic Process Automation (RPA), a subset of repetitive task automation is the use of computer software that is designed, according to digital task automation, to execute high-volume, routine or repetitive tasks within a job that were previously performed by a human according to predefined business rules.* This definition clearly outlined what RPA was (computer software), how it operated (execute on high-volume, routine or repetitive digital tasks according to business rules) and what it performed these operations on (tasks within a job that were previously performed by a human).

Step 2 Create sample items: Based on the literature review performed in step one, the practical experience of the researcher regarding RPA described in Section 4.2 of and consultations with RPA experts in industry, the following 9 items were generated for the scale:

Routine or repetitive tasks within my job have been replaced with RPA.

RPA enables me to accomplish my overall job objectives more effectively.

RPA allows me to spend more time on what I was employed to do.

RPA allows me to be more creative and innovative because my routine and repetitive tasks have been replaced by RPA.

RPA improves my job performance.

RPA improves my job productivity.

RPA improves my job effectiveness.

RPA makes it easier to do my job.

RPA allows me to spend more time on analysis, add value and make better job decisions.

Step 3 Collect data: A pilot study was administered, and data was collected. Johanson and Brooks (2010) suggest that a pilot test can be used to assess the quality of the scale and the pilot study is discussed in greater detail in the data gathering process in Section 4.6.2 of this study. According to Clark and Watson (1995), it was advised to administer the newly developed scale together with existing scales as part of the pilot study since it provided the opportunity to assess the boundaries of the new scale together with how it interacted with existing scales. It also provided an opportunity to assess whether these interactions are in line with the

theoretical conceptualisations of RPA that were hypothesised in the early stages of scale development. Therefore, due to time constraints, the RPA scale was administered as part of the pilot study for this research, and not separately.

The pilot study yielded 18 responses in total with 3 responses incomplete resulting in 15 completed responses. A sample size of 150 (Hinkin, 1995) was the minimum recommended for scale development in order to conduct Exploratory Factor Analysis (EFA) while other research suggested a sample sizes of between 50 and 100 (Carpenter, 2018) to enable EFA. Johanson and Brooks (2010) recommended a sample size of 30 for scale development since reliability measures showed little change with samples over 30 however, factor analysis was not considered as part of their assessments. The sample size achieved for the purposes of this study is a limitation to this process however, due to time constraints, this could not be avoided. Refer to Section 4.9 and 7.4 for further details.

Step 4 Purify the measure: The purpose of this step was to assess and refine the attributes of the scale using statistical techniques (Carpenter, 2018; Churchill, 1979). The results of the pilot study were assessed for validity and reliability using EFA and Cronbach's alpha coefficient respectively. This was the initial statistical tests to gain an understanding of the validity and reliability of the scale. Reliability measures using Cronbach's alpha coefficient resulted in a value of 0.96. Carpenter (2018) suggested that scales with high alpha coefficients may be indicative of item repetition or redundancy. However, Carpenter (2018) did not define what measurement range constituted a high reading. Literature and statistical sources regarding what constitute high alpha coefficient values differ with some sources suggesting that values greater than 0.90 may indicate item redundancy (Tavakol & Dennick, 2011) while others suggest that values greater than 0.95 may be problematic (Chen & Kraus, 2004; Goforth, 2015). It was therefore decided to continue with the process given this score of 0.96.

The newly developed scale also yielded a Kaiser-Meyer-Olkin (KMO) score for sampling adequacy of above 0.5 and a Bartlett test for sphericity of 0. Both these values suggested that the data was suitable for factor analysis. An EFA was run and resulted in 3 lower order constructs within RPA implying multidimensionality within the construct. These 3 lower order constructs were not conceptualised during step 2 of item generation as the researcher believed that all the items within the scale related to the higher order construct of RPA only (i.e. RPA was conceptualised as a

unidimensional construct). Since minimum sample sizes of between 100 and 150 were suggested in literature (Hinkin, 1995; Carpenter, 2018) for a successful EFA, it was therefore assumed that the multidimensionality extracted was attributed to a low sample size attained for the pilot test.

Sample sizes for a successful Confirmatory Factor Analysis (CFA) differ in literature where Beavers, Lounsbury, Richards, Huck, Skolits, & Esquivel, (2013) recommended a minimum of 150, Hinkin (1995) suggested a minimum of 200 and Worthington and Whittaker (2016) recommended a minimum sample size of 100. CFA was therefore not performed due to the inadequacy of the sample size. Furthermore, Carpenter (2018) suggested that an EFA is preferred over CFA for scale development since the assumptions that are made regarding the dimensionality of the scale may be inaccurate (due to the lack academic literature or newness of the construct being measured) and suggested that CFA be conducted at a later stage and separately from the results of EFA purely to confirm structure and model fit of the construct.

At this point of the process, due to time constraints and the relatively high internal consistency value the researcher decided to continue with the study using the conceptualised RPA measurement scale in its current state even though the high alpha coefficient may have been indicative of item redundancy. It was assumed that the requisite sample numbers that will be achieved during final data collection phase will yield the appropriate internal consistency, EFA and CFA model fit measures when the final statistical analysis is performed, and time constraints of the study prevented further refinement of the scale. Furthermore, the researcher was of the view that there were enough and appropriate levels of diligence demonstrated to conceptualise the RPA construct using practical experience and by a review of existing literature to warrant continuation of the study given the measurement scale in its current state. All statistical tests will be discussed and substantiated in greater detail in Section 4.8 of this study together with final reliability and validity calculations in Section 5.3 and 5.4 respectively followed by a discussion of the RPA scale Section 6.2.

Step 5 (collect data), **step 6** (reliability), **step 7** (validity) and **step 8** (develop norms): This will be discussed in detail in Sections 5.3, 5.4 and 6.4 of this study since the primary data collection and statistical analysis steps of scale development is common to the overall data collection and analysis of this research.

4.6.2 Pilot testing

Johanson and Brooks (2010) proposed that a pilot survey be administered to ensure that the constructs within the survey are valid and reliable from a face value perspective. Feedback from the pilot study helped to refine the survey questionnaire by removing ambiguity, clarifying certain areas of possible misinterpretation, improving the format of the survey and incorporating any other suggestions that may enhance the final questionnaire (Creswell, 2003; Johanson & Brooks, 2010; Saunders et al., 2009). This will allow for more accurate insights to be gained from the study. The extent of the pilot testing is dependent on the size of the survey and Saunders et al. (2009) suggested that a minimum of 10 responses is enough for small scale surveys with large scale surveys requiring between 100 and 200 responses.

A pilot survey was administered within the researcher's network with instructions to participants to provide feedback on completion times, clarity of instructions, ambiguity of questions, appropriateness of questions from a content and comfort perspective and the overall layout of the survey. 15 completed responses were received regarding the consistency of wording and grammatical errors that resulted in misinterpretation. There were no objectives regarding ambiguity, clarity or appropriateness of questions. These proposed changes were incorporated by the researcher and that the final measurement instrument was of a higher quality.

As discussed in step 3 in Section 4.6.5.1, this pilot study was also used to test the statistical validity and reliability of the RPA measurement scale developed for the purposes of this study. Clark and Watson (1995) suggested a two-tiered scale development testing process with an initial pilot test of between 100-200 respondents to test the item formats and a final test with a sample size of a minimum of 300 heterogeneous respondents in order to assess the validity and reliability of the newly developed measurement scale. This supports the sample size assertions by Beavers et al. (2013), Hinkin (1995) and Worthington and Whittaker (2016) for conducting a successful EFA's and CFA's. The two-tiered approach was corroborated by Carpenter (2018) where a pre-test with a sample of 100 was suggested before conducting a pilot test to refine the measure. Johanson and Brooks (2010) recommended a sample size of 30 for scale development since reliability measures

showed little change with samples over 30 however, factor analysis was not considered as part of their assessments.

Due to the cross-sectional nature of this study, time constraints prevented the researcher from approaching the scale development process using the above sampling rationale and the implications of this were discussed in step 4 (purify the measure) of the scale development process in Section 4.6 of this study together in Section 4.9 and 7.4.

4.7 Data gathering process

Following the pilot test, the instrument was refined and data gathering commenced. The survey was self-administered using an internet-based data collection tool called SurveyMonkey. According to Shuck et al. (2011), a self-administered, internet-based survey is the most widely used and cost effective data collection method for research, both from an academic and organisational perspective. This unobtrusive data collection method allows the respondent to complete the survey at his or her leisure and grants the respondent anonymity thereby improving the response rate (Zikmund et al., 2012).

A direct link to the questionnaire was shared with potential respondents within the researchers' network via email, instant messaging platforms (WhatsApp) and social media (LinkedIn). An introductory message briefly describing the survey and its purpose accompanied the direct link was shared to ensure that a level of professionalism was adhered to. A snowball sampling technique was used so that the survey reached additional respondents by requesting the initial respondents to forward the link to their respective networks. A follow up message was sent via email and WhatsApp and posted on LinkedIn as a reminder to complete the survey approximately a week before the survey was scheduled to close. The survey was opened for a month and a raw total of 213 responses was gathered.

4.8 Analysis approach

The raw data was downloaded from SurveyMonkey in an excel format so that analysis can begin. To reiterate, a study that utilises a quantitative research methodology employs specific statistical techniques to collect, analyse and interpret the data subsequently using this information to describe the results of the study (Creswell, 2003). However, before the data can be analysed and interpreted, it should be analysed for “completeness, consistency and legibility” (Zikmund et al., 2012, p.463) in a process called editing.

The excel file was analysed and the sample was segmented according to how respondents answered the screening question: *Are tasks within your job impacted by RPA?* Respondents who answered in the affirmative were separated from the others and this segmented data (for the affirmative responses) formed the sample on which analysis commenced. Missing data was identified and responses with less than a 50% completion rate were discarded in its entirety to ensure reliability of the data set while respondents with a completion rate of between 50 – 100% had data values imputed. Imputation is described as the filling in of a missing data point using a best guess method in order to obtain the most viable estimate and since the sample was assumed to be homogenous, this imputation method was deemed appropriate (Zikmund et al., 2012). The data was then imported into IBM SPSS and AMOS for statistical analysis.

4.8.1 Reliability

A measure is said to be reliable to the extent that it produced consistent results in independent tests (Churchill, 1979) and a reliable measure, which is free of random error, will demonstrate consistency in returning the true value of the measurement when used repeatedly (Zikmund et al., 2012). Therefore, the degree of reliability depended on the level of random error where perfect reliability meant random error equalled zero. If a measure proved to be valid, then reliability would have been proved also. However, the converse does not apply. A reliable measure does imply that it is valid, as differences in measurements could have been attributable to systematic errors or true differences (Churchill, 1979; Hair et al., 2010). Refer to Section 4.6 for further detail.

Cronbach's Alpha, which demonstrates convergence of items within a measure on a scale from 0 to 1, is the most commonly used statistical technique to assess reliability by quantifying the internal consistency and of a measure (Saunders et al., 2009; Zikmund et al., 2012). Internal consistency values of 0.6 – 0.7 are acceptable at the lower limits (Hair et al., 2010) however, for the purposes of this study, internal consistency values above 0.7 were deemed acceptable.

All measurement scales used in this study, except the measurement scale for RPA which was developed by the researcher (refer to Section 4.6 for further details) were adapted from previous reputable research. The RPA measurement scale was developed according to scale development theory and techniques (Carpenter, 2018; Churchill, 1979; Hinkin, 1995; Reidenbach & Robin, 1990; Tay & Jebb, 2016; Worthington & Whittaker, 2016) and reliability was assessed during the development phase (Refer to step 4 of scale development: purify the measure in Section 4.6.5.1). Reliability values for the constructs used in this study are as follows:

Meaningfulness (May et al., 2004): $\alpha = 0.90$

DE (Lloyd, 2008): $\alpha = 0.87$

ITT (Colarelli, 1984): $\alpha = 0.75$

RPA (authors own): $\alpha = 0.85$ (revised score, refer to Section 6.4 for further detail)

To ensure that the above reliability measure was not diluted within the context of this study, the Cronbach's Alpha value for all the above measurement scales were reassessed when inferential statistics were performed. (Please refer to Section 5.3 for further details).

4.8.2 Validity

As described in Section 4.6 of this study, Churchill's (1979) explanation of error types that are associated with measurement scales created the perfect theoretical underpinnings to understand the concept of validity and its interplay with reliability. Systematic and random errors erode the level of validity and reliability within a measure (Bagozzi & Phillips, 1991; Hair et al., 2010; Churchill, 1979). As described in Section 4.8.2, the extent to which a measure is reliable is dependent on the level of random error (Churchill, 1979). Validity is described as the extent to which a

measure accurately reflects the theoretical concept of a construct and is therefore dependent on the level of systematic error within the measure (Bagozzi & Phillips, 1991; Churchill, 1979; Zikmund et al., 2012).

The statistical technique of Principal Component Analysis (PCA) was used to understand the interrelationships among the variables. Before the researcher proceeded with factor analysis, the data had to be assessed for factorability (Hair et al., 2010). The correlation matrix of variables was tested to ensure that correlations existed between variables with an r measure of at least 0.30. (Refer to Section 4.8.3 for further detail regarding correlation). The statistical significance of these correlations had to be tested to ensure a level significance using the Bartlett test for sphericity and a sig value of $p < 0.05$ indicated statistical significance of the correlations. Finally, in order to confirm the correlations among variables, a Kaiser-Meyer-Olkin (KMO) test was performed as a measure of sampling adequacy with a minimum value of 0.50 that's required. Once these 3 requirements were met, the data was deemed suitable for factorability (Beavers et al., 2013; Hair et al., 2010; Zikmund et al., 2012).

In order to determine the number of factors that may exist within the variables, EFA was conducted by the researcher as a data reduction technique (Beavers et al., 2013). Once this was ascertained, CFA was conducted to assess overall model fit by testing how well the variables are representative of the constructs (Hair et al., 2010) and provided an indication of goodness of fit as follows: Root Mean Square of Approximation (RMSEA) where a value of < 0.06 represented a good fit (Hair et al., 2010) and the Standardised Root Mean Squared Residual (SRMR) where a value of < 0.08 represented a good fit (May et al., 2004).

According to Zikmund et al. (2012) CFA is also useful to assess construct validity. Construct validity is described as the extent to which variables are theoretically representative of the construct that it was designed to measure (Hair et al., 2010). Convergent validity and discriminant validity are subsets of construct validity. Convergent validity describes the extent to which item measures shared a high level of common variance or relation with each other. For high levels of convergence, the relationship or factor loadings between the variable and construct should be greater than 0.7 and the Average Variance Extracted (AVE) should be greater than or equal to 0.5 (Hair et al., 2010).

Discriminant validity describes the level of uniqueness within a measure (Zikmund et al., 2012). High levels of discriminant validity exist where a measure does not share a strong correlation with a measure of another construct. In order to assess the levels of discriminant validity, the researcher analysed cross loadings between measured variables and other constructs that they correlated to. High cross loadings imply that discriminant validity may be jeopardised (Hair et al., 2010).

4.8.2 Descriptive and inferential statistics

Descriptive statistics

Descriptive statistics is a precursor to inferential stats and is defined as a technique used to describe data in terms of specific attributes so that the sample can be profiled (Zikmund et al., 2012). Sample population descriptive statistics outline attributes that can enhance the profiling of data including details of the respondents' education, age, positions within their organisation, tenure, size of the organisation and industry. Descriptive statistics were presented in a tabular format.

Measures of central location and dispersion provide important descriptive properties (Wegner, 2016). Central location measures such as the mean and median provide a single number that describes the centrality of data. The mean or average, computed by adding data values together and dividing by the sample size, is different to the median which is the middle number in a data set. Measures of dispersion such as variance describe how the data is located about the central location measure (Wegner, 2016). Descriptive statistics ensured that the final constructs are statistically described for mean, variance, skewness and kurtosis after reliability and validity assessments were conducted.

Inferential statistics

The purpose of inferential statistics is to draw inferences on the mediating effect of meaningfulness on the relationship between RPA and the outcome variables on the entire knowledge worker population. This is based on the outcome of statistical tests, via the research hypotheses, on the sample of data within this study that serves as a proxy for the broader knowledge worker population (Creswell, 2003; Wegner, 2016;

Zikmund et al., 2012). To test the research hypotheses, the researcher used a first-generation statistical procedure, as this is the most commonly used multivariate statistical technique adopted in exploratory analysis for a theory testing process (Guarino, 2004).

Each of the proposed research hypotheses were analysed through a multivariate analytical lens as the researcher suggested specific relationships to exist which needed to be statistically evaluated. Prior to using any inferential statistical procedures, the researcher needed verify whether the data is normally distributed or not as this guided the decision as to whether parametric or non-parametric tests should be adopted (Zikmund et al., 2012). A Shapiro-Wilk test was conducted to ascertain how the data was distributed since the sample size was less than 1000 (Shapiro & Wilk, 1965). A $p > 0.05$ implies that the data is normally distributed thereby using parametric testing procedures alternatively, $p < 0.05$ implies data that is not normally distributed resulting in the adoption of non-parametric tests.

The purpose of this research was to understand how an emerging technology in the form of RPA, influenced voluntary work outcomes of DE and ITT, that are strongly associated with organisational performance, of knowledge workers. Statistically, this involved establishing if relationships existed between the independent variable (RPA) and the dependent variables (DE and ITT). Once these relationships are established, the researcher sought to understand if meaningfulness intervened and was responsible for explaining why these relationships existed and if so, to what extent. The statistical procedures described below explain how testing for an intervening variable is performed.

Moderation and mediation

Two methods exist to understand the impact of an intervening variable on the relationship between a predictor variable (independent) and outcome variable (dependent), mediation and moderation, and researchers often confuse these terms with each other (Baron & Kenny, 1986). Moderation evaluates “whether the *magnitude* of a variables effect on some outcome variable of interest depends on a third variable” (Hayes, 2012, p. 4). Mediation evaluates whether the relationship between the predictor and outcome variables is *explained* by or occurs through a

mediator (Hayes, 2012). The moderation model, together with paths, is represented graphically below:

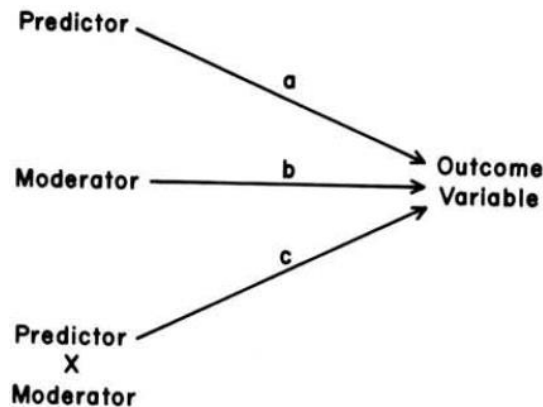


Figure 7: Moderation model

Adapted from: “The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations,” by R.M. Baron and D.A. Kenny, 1986, *Journal of personality and social psychology*, 51(6), p. 1174. Copyright 1986 by American Psychological Association, Inc.

As per the above path diagram, significant or non-significant relationships exist between the predictor variable, moderator and the outcome variable (**path a and b**). As per Figure 7 above, the moderation model will hold true if **path c** (moderator x predictor) is significant irrespective of whether path a and c was significant in the first place. In the context of this research this will mean that relationships between RPA and the outcome variables of DE and ITT will exist, however, when the effects of RPA and meaningfulness are multiplied and produces a significant relationship, then meaningfulness is said to moderate or strengthen the relationship between RPA and the outcome variables. Meaningfulness will also not need to be present for the relationship between RPA and the outcome variables to exist (Barron & Kenny, 1986).

The most appropriate way to describe mediation is one “which recognizes that an active organism intervenes between stimulus and response” (Baron & Kenny, 1986, p. 1176). The effects of the stimuli (independent variable) is mediated by transformational processes within the active organism (mediator) that will result in an outcome or response (dependent variable). Within the context of this study, the

stimulus (RPA) is mediated by transformational processes within the active organism (meaningfulness) to produce a response (DE and ITT). The mediation model is represented graphically below:

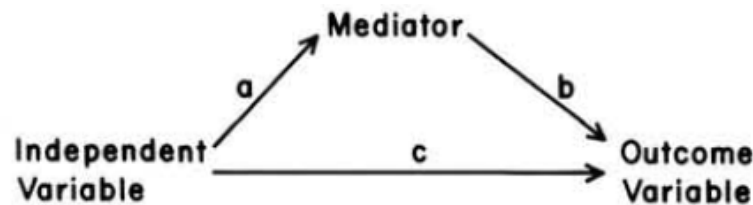


Figure 8: Mediator model

Adapted from: "The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations," by R.M. Baron and D.A. Kenny, 1986, *Journal of personality and social psychology*, 51(6), p. 1176. Copyright 1986 by American Psychological Association, Inc.

If a variable explains the existence of a relationship between an independent and dependent variable, then that variable is said to be a mediator variable. A mediator variable will explain *how or why* a relationship exists (from the perspective of psychological significance) as opposed to a moderator variable that defines *when* a relationship will exist (Baron & Kenny, 1986). For the mediation model to hold true multiple techniques can be used (Baron & Kenny, 1986; Preacher & Hayes, 2004).

The path significance method (Baron & Kenny, 1986) states that significant relationships must exist along **path a** in Figure 8 above, **path b** and **path c**. However, in the presence of path a and b, the relationship between the independent and outcome variable (**path c**) should be insignificant. If path c is zero, then the relationship is fully mediated by the mediator variable. If path c is not zero, then this could imply the existence of another mediating variable that will explain why the relationship exists.

Alternatively, Preacher and Hayes (2004) assert that for mediation to exist, the independent variable needs to exert a statistically significant effect on the dependent variable indirectly via the mediator (paths a and b) and the mediation effect size of the mediator will be interpreted as the proportion of the variance accounted for (VAF) in the dependent variable as a result of the independent variable (Hayes, 2009). Both techniques require a statistically significant relationship to exist between the

independent and dependent variables known as the direct effect. The effect of the independent variable on the dependent variable via the mediator is referred to as the indirect effect. VAF is calculated as indirect effect + total effect [where total effect ($a + b + c$) = direct (c) + indirect effect ($a + b$)]. VAF values that exceed 20% but are less than 80% indicate partial mediation. Where VAF values exceed 80%, total, full or complete mediation is said to have occurred.

For the purposes of this study, a mediation model was adopted because the researcher wanted to explain *how* and *why* exposure to RPA will result in increased DE levels and reduced intention to leave. This effect that RPA has on DE and ITT may be explained partially or in its entirety by the psychological condition of meaningfulness (Kahn, 1990) via a process of sensemaking (Aguinis & Glavas, 2019).

Linear relationships between variables were measured using correlation analysis (r) which represents the effect size. An effect size is described as the extent to which a phenomenon exists within a population (Hair et al., 2010) and is considered the most important measurement in a quantitative study (Sullivan & Feinn, 2012). Within the context of a linear relationship, the effect size will determine the strength of correlation between variables with a measurement from negative 1 to positive 1 where $-1 < r < 0$ denoted a negative relationship that became weaker approaching -1, $r = 0$ denoted no relationship and $0 < r < 1$ denoted a positive relationship that became stronger approaching 1 (Wegner, 2016).

Sullivan and Feinn (2012) assert that correlation effect sizes based on Cohen's D are small ($+/-0.2$), medium ($+/-0.5$) and large ($+/- 0.8$). The Pearson correlation technique was considered as the primary method to measure correlation however, the following assumptions had to hold true: (1) the scale on which the variables were measured had to be continuous, (2) each variable had to be measured, (3) linear relationship has to exist between variables, (4) no significant outliers should exist and (5) the data needs to be normally distributed. In the absence of data normality, the Spearman rank correlation technique would be appropriate (Bonnet & Wright, 2000; Hair et al., 2010; Zikmund et al., 2012). The Spearman technique has 3 assumptions that must be met. The first 2 assumptions are shared with assumption 1 and 2 of the Pearson technique with the third assumption being the existence of a monotonic relationship between the variables.

Multiple linear regression analysis was the primary statistical technique used to analyse the relationship between the independent variable (RPA) and the dependent variables (DE and ITT). The key difference between a correlation and multiple regression analysis is the concept of *dependence* where a correlation analysis technique is impartial to dependence (Hair et al., 2010; Zikmund et al., 2012). According to Hair et al. 2010, the success of multiple regression analysis is dependent on the following assumptions holding true: (1) the existence of a linear relationship between the dependent and independent variables, (2) constant variance (no unequal variances or heteroscedasticity), (3) independence (predicated values from the model is independent and unrelated to other predications), (4) normality (dependent and independent variables are normally distributed) and (5) multicollinearity to ensure that the independent variables are not interrelated with each other (Cortina, 1993). A Variance Inflation Factor (VIF) was computed to ensure that no multicollinearity existed (Zikmund et al., 2012). Acceptable VIF factors have been assessed at a minimum of 5.0 (Zikmund et al., 2012) and a maximum of 10 (Hair et al., 2010). For the purposes of this study, a VIF factor of 10 was used as the cut-off point at which point multicollinearity may become an issue.

To assess the mediating effect of meaningfulness on the relationship between RPA and the outcome variables of DE and ITT, the Preacher and Hayes method was adopted and Model 4 from Hayes model templates for SPSS was used (Hayes, 2013). The proposed model was then tested via a mediated regression analysis (Baron & Kenny, 1986). The statistical rationale of Model 4 is graphically represented by the following statistical diagram:

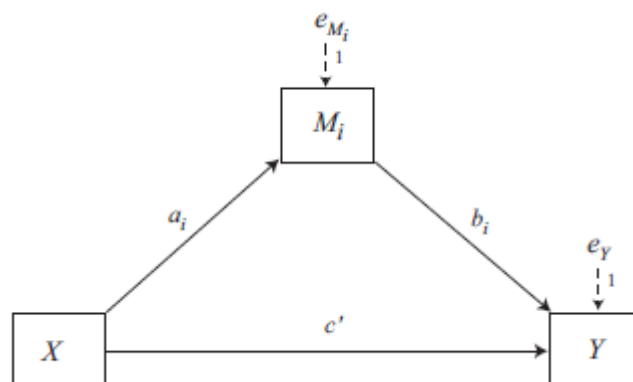


Figure 9: Statistical Mediator Model (Model 4)

Adapted from: "Model Templates for PROCESS for SPSS and SAS," by A.F. Hayes, 2013, p. 4. Copyright 2013 by Andrew F. Hayes, <http://www.afhayes.com/>

As per the statistical mediation model in Figure 9 above, X represents the stimulus or independent variable (RPA), Y represents the outcome or dependent variable (DE or ITT) and M_i represents the organism or mediator (meaningfulness) via which X will impact Y (Baron & Kenny, 1986). For mediation to exist, RPA (X) needs to exert a statistically significant effect on DE or ITT (Y) indirectly via meaningfulness (M_i) (Preacher & Hayes, 2004). The mediation effect size of meaningfulness (M_i) will be interpreted as the proportion of the variance accounted for (VAF) in DE and ITT (Y) as a result of the indirect effect of RPA (X) (Hayes, 2009; Preacher & Hayes, 2008). VAF is calculated as indirect effect + total effect (where total effect = direct + indirect effect). By following the path diagram in Figure 9, VAF is calculated as $[(a_i \times b_i) + (c' + (a_i \times b_i))]$. As discussed in above, VAF values that exceed 20% but are less than 80% indicate partial mediation and this indicates the existence of additional mediators. Where the VAF values exceed 80%, total, full or complete mediation is said to have occurred.

4.9 Limitations

The most significant limitation to the methodology was the inadequacy of the sample size used during the pilot testing phase of the scale development process ($n = 15$). The purpose of the pilot testing from a scale development perspective was to refine the scale to ensure high levels of validity and reliability for the final instrument. This was exclusively attributed to the time constraints experienced by the researcher for completion of the study. With the exception of Johanson and Brooks (2010) who proposed a sample size of 30 due to factor analysis not being incorporated in their assessment, all other research proposed sample sizes between 50 and 300 (Carpenter, 2018; Churchill, 1979; Clark & Watson, 1995; Hinkin, 1995; Worthington and Whittaker, 2016) and suggested that the larger the sample size in the testing and refinement phase of scale development, the greater validity and reliability the scale will possess.

During step 4 of the scale development process (purify the measure), EFA resulted in inaccurate dimensionality of the RPA construct with 3 factors being extracted. This put the refinement phase of the development process at risk as the researcher was unsure whether items should be removed or added to the scale to improve its validity.

Subsequent analysis with appropriate sample sizes however yielded correct EFA measures and established the validity and reliability of the scale.

A sampling bias may have been introduced as respondents may have shared similar characteristics as the survey was snowballed to additional respondents. Furthermore, an internet-based survey will also contribute to sampling bias since the researcher does did not have control over the distribution of the survey.

CHAPTER 5: RESULTS

5.1 Introduction

The objective of this chapter is to provide the results to the research hypotheses discussed in Chapter 2 and 3 through the research design and analytical approach adopted in Chapter 4. This chapter begins by providing descriptive analysis on the sample size achieved and specific sample population descriptive that was included in the measurement instrument. Thereafter reliability and validity measures are presented which is followed by inferential statistics, the aim of which was to understand if any mediating effect exists by meaningfulness on the relationship between RPA and the outcome variables of DE and ITT.

5.2 Descriptive characteristics of sample data

5.2.1 Research sample

Table 4: Sample descriptive characteristics

Attribute	Total
Raw sample size	213
Screened out (eligibility)	86
Respondents with less than 50% completion	7
Respondents with 100% completion	110
Respondents with between 50 - 100% completion	10
Data points imputed for	43
Final sample size	120

The researcher initially sought to obtain a minimum sample size of 200 as described in Section 4.5 of this study. Table 4 above summarises the descriptive characteristics of the raw sample size achieved for this research. A raw sample size of 213 was achieved for this research study however, 86 respondents were disqualified as they answered screening question in the negative – “*Are tasks within your job impacted by RPA?*”. These 86 respondents were disqualified as they did not form part of the unit of analysis within the scope of this research as described in Section 4.4 of this study. A further seven respondents were removed as they reported a survey

completion rate less than 50%. Data imputation was conducted on a further 10 respondents who reported a survey completion rate of between 50 – 100%. The final qualifying sample size obtained for this research was 120. In comparison, other research of similar design by Saks (2006) and May et al. (2004) obtained final sample sizes of 102 and 213 respectively. The researcher deemed a sample size of 120 adequate for this research based on the minimum of 90 that was required for the statistical analysis (refer to Section 4.5 for target sample size calculation).

5.2.2 Respondents

Table 5: Age of respondents

Age		
Category	Frequency	Percent
18- 24	4	3.3
25 - 34	42	35.0
35 - 44	46	38.3
45 - 54	23	19.2
55 - 64	4	3.3
>65	1	0.8
Total	120	100.0

The researcher included a total of six descriptive questions in the measurement instrument as discussed in Section 4.6. Table 5 above provides a summary of the age groups in which each of the survey respondents identified. 38.3% of the respondents reported their age as being between 35 – 44 years, a further 35% reported their age group as being between 25 – 34 years, 19.2% reported their age group between 45 – 54 years and less than 7.4% reported their age groups between 18 – 24 years (3.3%), 55 – 64 years (3.3%) and over 65 years (0.8%).

Table 6: Job level of respondents

Job level		
Category	Frequency	Percent
Junior staff	11	9.2
Team lead	9	7.5
Specialist	25	20.8
Middle manager	23	19.2
Senior manager	33	27.5
Executive	13	10.8
Other	6	5.0
Total	120	100

Table 6 above provides a summary on the job levels that each of the survey respondents reported. 27.5% of the respondents indicated that they were at a senior management level, a further 20.8% indicated that they were in specialist roles, 19.2% indicated that they were at a middle management level, whilst 10.8 reported that they were in executive roles. The other job level categories reported less than 10% each with 9.2% of the respondents indicating that they were junior staff, 7.5% as team leads and 5% reported that they were in other job roles which were not identified by the survey options for this descriptive question.

Table 7: Education level of respondents

Education level		
Category	Frequency	Percent
Matric	11	9.2
Diploma	15	12.5
Bachelor's degree	20	16.7
Honours degree	24	20.0
Master's degree	37	30.8
PhD	3	2.5
Professional designation	5	4.2
Other	4	3.3
Missing	1	0.8
Total	120	100.0

The researcher included an educational level descriptive question to gain an understanding of how qualified the knowledge workers with this sample were. This

question was used only for a descriptive purpose within the scope of this research. According to Table 7 above, 53.3% of the respondents indicated that they had post-graduate qualifications (PhD, masters and honours degrees), 16.7% indicated that they had a bachelor's degree, 12.5% reported that they had a diploma and 9.2% reported that they had a matric qualification only. Four respondents indicated that they had other educational levels not identified by the researcher and 1 respondent failed to provide an option.

Table 8: Tenure at the organisation

Tenure		
Category	Frequency	Percent
< 1 year	23	19.2
1 - 5 years	34	28.3
5 - 10 years	29	24.2
> 10 years	34	28.3
Total	120	100.0

As illustrated in Table 8 above, 28.3% of the respondents indicated that their tenure at their current organisation was in excess of 10 years and between one and five years respectively. 24.2% of the respondents reported their tenure as between 5 and 10 years whilst 19.2% indicated less than a year at their current organisation.

Table 9: Industry

Industry		
Category	Frequency	Percent
Education	1	0.8
Finance	31	25.8
Manufacturing	8	6.7
Mining	31	25.8
Telecommunications	28	23.3
Utilities (electricity or water)	2	1.7
Other	18	15.0
Missing	1	0.8
Total	120	100.0

The researcher sought to gain a descriptive understanding of the industries in which the sample population are currently employed in as described in Table 9 above. This provides an understanding of which industries are the most impacted by RPA within the context of the sample.

Table 10: Knowledge worker job type results

Task Type	Sample Response	
Routine Tasks (Easily Automatable)	20 (16,7%)	37 (30,8%)
Abstract Tasks (Not easily Automatable)	63 (52,5%)	

Finally, the researcher sought to gain an understanding of the type of tasks the knowledge worker sample performs. As per the matrix in Figure 1 in Section 2.2.2, Davenport (2011) categorised knowledge work into 4 quadrants, based on whether it is routine, repeatable, improvisational or requires judgement. He also categorised knowledge work that can be performed individually or requires collaboration. By triangulating literature by Autor (2015), Autor and Price (2013) and Davenport (2011), the researcher developed Table 3 to broadly group tasks for the purposes of this study. The measurement instrument requested respondents to choose two work types that best described their daily work. According to the researcher's grouping in Table 10 above, 16.7% of the sample categorised their work as routine (easily automatable), 52.5% categorised their work as abstract (not easily automatable) and 30.8% of the sample performed work with tasks that are both routine and abstract. The implications of this are discussed in Chapter 6 and Section 6.4 of this study.

5.3 Reliability

Table 11: Reliability

Scale	Number of items after to Cronbach alpha	Number of items prior to Cronbach alpha	Cronbach Alpha
Meaningfulness	6	6	0.92
RPA	5	9	0.89
DE	7	7	0.91
ITT	3	3	0.78

Reliability of the latent variables was assessed by evaluating its level of internal consistency. The statistical measure that was used to evaluate internal consistency is Cronbach's alpha. As per Table 11 above, all the latent variables reported Cronbach alpha scores > 0.7 which is the acceptable threshold for the purposes of this research (Hinkin, 1995). The meaningfulness latent variable reported the highest score at 0.92 and the ITT reported the lowest at 0.78. The RPA latent variable initially reported a score of 0.96 which may be indicative of item redundancy (Carpenter, 2018; Chen & Kraus, 2004; Goforth, 2015; Tavakol & Dennick, 2011). Items within the scale were reassessed and 4 items were removed for possible redundancy issues. The revised scale returned a score of 0.89 which was deemed acceptable (refer to Section 6.4 for further detail).

Due to its academic infancy, the RPA measurement scale was developed according to scale development theory (Carpenter, 2018; Churchill, 1979; Hinkin, 1995; Reidenbach & Robin, 1990; Tay & Jebb, 2016; Worthington & Whittaker, 2016) as no measurement scale existed for the purposes of this research. (please refer to Section 4.6 for further details regarding the scale development and Section 6.4 for a discussion of the scale). Measurement scales for the other constructs were adapted from existing literature. May et al. (2004) reported a Cronbach alpha score of 0.90 for meaningfulness, Lloyd (2008) reported a score of 0.87 for DE and Colarelli (1984) reported a score of 0.75 for ITT.

5.4 Validity

Table 12: Convergent and discriminant validity (Meaningfulness)

	Mean1	Mean2	Mean3	Mean4	Mean5	Mean6
Mean1	1.0					
Mean2	0.58	1.0				
Mean3	0.70	0.6	1.0			
Mean4	0.69	0.7	0.9	1.0		
Mean5	0.68	0.8	0.8	0.9	1.0	
Mean6	0.59	0.4	0.6	0.6	0.6	1.0
DE1	0.36	0.4	0.4	0.4	0.4	0.3
DE2	0.29	0.2	0.4	0.3	0.3	0.4
DE3	0.34	0.3	0.4	0.3	0.3	0.2
DE4	0.36	0.4	0.4	0.3	0.3	0.3
DE5	0.46	0.3	0.6	0.5	0.5	0.5
DE6	0.36	0.3	0.5	0.4	0.4	0.4
DE7	0.33	0.3	0.4	0.4	0.3	0.2
ITT1	-0.39	-0.3	-0.4	-0.4	-0.4	-0.2
ITT2	-0.34	-0.2	-0.3	-0.3	-0.3	-0.1
ITT3rc	-0.37	-0.3	-0.4	-0.4	-0.5	-0.2
RPA1	-0.01	0.1	0.0	0.0	0.0	0.1
RPA2	0.06	0.1	0.2	0.1	0.2	0.2
RPA4	0.13	0.1	0.3	0.2	0.2	0.2
RPA6	0.07	0.0	0.2	0.1	0.2	0.2
RPA7	0.11	0.0	0.2	0.1	0.2	0.2

Table 13: Convergent and discriminant validity (DE)

	DE1	DE2	DE3	DE4	DE5	DE6	DE7
Mean1	0.4	0.3	0.3	0.4	0.5	0.4	0.3
Mean2	0.4	0.2	0.3	0.4	0.3	0.3	0.3
Mean3	0.4	0.4	0.4	0.4	0.6	0.5	0.4
Mean4	0.4	0.3	0.3	0.3	0.5	0.4	0.4
Mean5	0.4	0.3	0.3	0.3	0.5	0.4	0.3
Mean6	0.3	0.4	0.2	0.3	0.5	0.4	0.2
DE1	1.0	0.6	0.7	0.8	0.5	0.4	0.6
DE2	0.6	1.0	0.4	0.6	0.5	0.5	0.4
DE3	0.7	0.4	1.0	0.8	0.6	0.5	0.7
DE4	0.8	0.6	0.8	1.0	0.6	0.5	0.7
DE5	0.5	0.5	0.6	0.6	1.0	0.8	0.5
DE6	0.4	0.5	0.5	0.5	0.8	1.0	0.5
DE7	0.6	0.4	0.7	0.7	0.5	0.5	1.0
ITT1	-0.3	-0.3	-0.2	-0.3	-0.2	-0.1	-0.3
ITT2	-0.2	-0.3	-0.1	-0.3	-0.1	0.0	-0.1
ITT3rc	-0.4	-0.2	-0.2	-0.3	-0.2	-0.2	-0.3
RPA1	0.1	-0.1	0.0	0.0	0.0	-0.1	-0.1
RPA2	-0.1	-0.1	-0.1	-0.1	0.1	0.1	-0.1
RPA4	-0.1	0.0	-0.1	0.0	0.1	0.1	0.0
RPA6	-0.1	0.0	-0.1	-0.1	0.1	0.1	0.0
RPA7	-0.1	0.0	-0.1	-0.1	0.1	0.1	0.0

Table 14: Convergent and discriminant validity (ITT)

	ITT1	ITT2	ITT3rc
Mean1	-0.4	-0.3	-0.4
Mean2	-0.3	-0.2	-0.3
Mean3	-0.4	-0.3	-0.4
Mean4	-0.4	-0.3	-0.4
Mean5	-0.4	-0.3	-0.5
Mean6	-0.2	-0.1	-0.2
DE1	-0.3	-0.2	-0.4
DE2	-0.3	-0.3	-0.2
DE3	-0.2	-0.1	-0.2
DE4	-0.3	-0.3	-0.3
DE5	-0.2	-0.1	-0.2
DE6	-0.1	0.0	-0.2
DE7	-0.3	-0.1	-0.3
ITT1	1.0	0.7	0.5
ITT2	0.7	1.0	0.5
ITT3rc	0.5	0.5	1.0
RPA1	0.0	-0.2	0.0
RPA2	-0.1	-0.1	-0.2
RPA4	-0.1	-0.2	-0.2
RPA6	0.0	-0.1	-0.2
RPA7	-0.1	-0.1	-0.2

Table 15: Convergent and discriminant validity (RPA)

	RPA1	RPA2	RPA4	RPA6	RPA7
Mean1	0.0	0.1	0.1	0.1	0.1
Mean2	0.1	0.1	0.1	0.0	0.0
Mean3	0.0	0.2	0.3	0.2	0.2
Mean4	0.0	0.1	0.2	0.1	0.1
Mean5	0.0	0.2	0.2	0.2	0.2
Mean6	0.1	0.2	0.2	0.2	0.2
DE1	0.1	-0.1	-0.1	-0.1	-0.1
DE2	-0.1	-0.1	0.0	0.0	0.0
DE3	0.0	-0.1	-0.1	-0.1	-0.1
DE4	0.0	-0.1	0.0	-0.1	-0.1
DE5	0.0	0.1	0.1	0.1	0.1
DE6	-0.1	0.1	0.1	0.1	0.1
DE7	-0.1	-0.1	0.0	0.0	0.0
ITT1	0.0	-0.1	-0.1	0.0	-0.1
ITT2	-0.2	-0.1	-0.2	-0.1	-0.1
ITT3rc	0.0	-0.2	-0.2	-0.2	-0.2
RPA1	1.0	0.5	0.3	0.3	0.3
RPA2	0.5	1.0	0.7	0.8	0.8
RPA4	0.3	0.7	1.0	0.8	0.8
RPA6	0.3	0.8	0.8	1.0	0.9
RPA7	0.3	0.8	0.8	0.9	1.0

5.5 Factor analysis

Table 16: Confirmatory factor analysis

Scale	CFA			
	SRMR	RMSEA	CFI	Chi-Square
Meaningfulness	0.04	0.15	0.96	0
DE	0.08	0.24	0.84	0
ITT				
RPA	0.04	0.19	0.92	0

The researcher conducted a CFA to evaluate the overall model fit for the research model. Table 16 above provides a summary of the CFA results. The ITT indices could not be calculated due to the small sample size of 120 achieved for this research. Sample sizes for a successful CFA differ in literature where Beavers et al. (2013) recommend a minimum of 150, Hinkin (1995) suggest a minimum of 200 and Worthington and Whittaker (2016) recommend a minimum sample size of 100. Even though the SRMR indicated good model fit scores ($SRMR < 0.08$), the RMSEA values were above the minimum threshold of 0.08. All CFI indices apart from DE reported indices > 0.9 . The Chi-Square probability for all the latent variables was < 0.05 which was insignificant. Based on these results the researcher further conducted a PCA to assess the model fit (Beavers et al., 2013).

Table 17: PCA

Construct	KMO		Bartlett's test of Sphericity	Number of Components extracted	Cumulative %
Meaningfulness	0.89	Meritorious	0.00	1	73.23
DE	0.84	Meritorious	0.00	1	65.02
ITT	0.67	Mediocre	0.00	1	69.55
RPA	0.81	Meritorious	0.00	1	71.71

Table 17 above summarises the results obtained from the PCA. All latent variables reported at least one correlation coefficient > 0.3 as illustrated in Tables 12 to 15. Furthermore, all KMO scores were > 0.5 indicating good sampling adequacy. Meaningfulness, DE and RPA reported KMO scores which were classified as meritorious whilst ITT reported a KMO score which was classified as mediocre. The Bartlett's test for sphericity reported a significance level of < 0.05 which verified that a PCA was suitable. All latent variables extracted one component each which was in line with the theoretical foundations, especially for the RPA scale developed for the purposes of this research. Based on these results, the researcher deemed the model fit adequate and hence moved on to evaluating the research hypotheses.

5.6 Construct descriptive statistics

Table 18: Descriptive statistics

Descriptive Statistics					
Construct	N	Mean	Std. Deviation	Skewness	
	Statistic	Statistic	Statistic	Statistic	Std. Error
Meaningfulness	120	1.80	0.68	0.90	0.22
DE	120	1.84	0.73	0.84	0.22
ITT	120	4.69	1.53	-0.54	0.22
RPA	120	2.82	1.23	0.91	0.22

Table 18 above provides a summary of the descriptive statistics for each of the latent variables. The scores for the latent variables of meaningfulness, DE, ITT and RPA were measured on a 7-point Likert scale ranging in value from 1-7, with 1 denoting

strongly agree and 7 denoting strongly disagree. The maximum possible average is therefore 7 (strongly disagree) and the minimum possible average is 1 (strongly agree). The latent variable ITT reported the largest mean of 4.69 and had the largest dispersion of data around the mean with a standard deviation of 1.53. Meaningfulness had the lowest mean of 1.80 with the least amount of dispersion around the mean with a standard deviation of 0.68.

Table 19: Tests for normality

Tests of Normality			
Construct	Shapiro-Wilk		
	Statistic	df	Sig.
Meaningfulness	0.89	120	0.00
DE	0.90	120	0.00
ITT	0.95	120	0.00
RPA	0.93	120	0.00

Furthermore, the distribution of the data was tested for normality using the Shapiro-Wilk and the results are summarized in Table 19 above. The test returned p values of < 0.05 and hence the null hypothesis that the population is normally distributed is rejected.

5.7 Assessment of research hypotheses

The Spearman's rank order test was used to test for associations between RPA and meaningfulness, DE and TT (hypotheses 1 to 5). This non-parametric statistical technique was used as the data was reported as **not** being approximately normally distributed (refer to the Table 20 in Section 5.6 of this study). The mediation tests between RPA, meaningfulness, DE and ITT (hypotheses 6 and 7) was assessed using a mediated regression model.

5.7.1 Hypothesis 1

Hypothesis one sought to establish if a positive relationship existed between RPA and meaningfulness though the following hypothesis:

H₀: There is no relationship between RPA and meaningfulness

H₁: There is a positive relationship between RPA and meaningfulness

Table 20: Correlation test: RPA and meaningfulness

Correlations			
Hypothesis 1		RPA	Meaningfulness
RPA	Correlation Coefficient	1	.23**
	Sig. (2-tailed)		0.01
	N	120	120

From Table 20 above, the Spearman's rank order test reported a positive correlation coefficient of 0.23, which was significant at the 95% confidence interval, between RPA and meaningfulness. The correlation coefficient was classified as a small effect ($0.1 < r < 0.3$). Furthermore, the relationship between RPA and meaningfulness was classified as monotonic through a visual assessment of the scatter plot (Appendix B, Figure 13). **Therefore, the null for hypothesis one was rejected** at a 5% level of significance and hence it can be concluded that a significant, positive relationship exists between RPA and meaningfulness based on the results of the Spearman's rank order test.

5.7.2 Hypothesis 2

Hypothesis two sought to establish if a positive relationship existed between meaningfulness and DE through the following hypothesis:

H₀: There is no relationship between meaningfulness and DE

H₂: There is a positive relationship between meaningfulness and DE

Table 21: Correlation test: meaningfulness and DE

Correlations			
Hypothesis 2		Meaningfulness	DE
Meaningfulness	Correlation Coefficient	1	.51**
	Sig. (2-tailed)		0.00
	N	120	120

From Table 21 above, the Spearman's rank order test reported a positive correlation coefficient of 0.51, which was significant at the 95% confidence interval, between meaningfulness and DE. The correlation coefficient was further classified as a large effect ($r > 0.5$). Furthermore, the relationship between meaningfulness and DE was classified as monotonic through a visual assessment of the scatter plot (Appendix B, Figure 15). **Therefore, the null for hypothesis two was rejected** at a 5% level of significance and hence it can be concluded that a significant, positive relationship exists between meaningfulness and DE based on the results of the Spearman's rank order test.

5.7.3 Hypothesis 3

Hypothesis three sought to establish if a negative relationship existed between meaningfulness and ITT through the following hypothesis:

H₀: There is no relationship between meaningfulness and ITT

H₃: There is a negative relationship between meaningfulness and ITT

Table 22: Correlation test: meaningfulness and ITT

Correlations			
Hypothesis 3		Meaningfulness	ITT
Meaningfulness	Correlation Coefficient	1	-.39**
	Sig. (2-tailed)		0.00
	N	120	120

From Table 22 above, the Spearman's rank order test reported a negative correlation coefficient of -0.39, which was significant at the 95% confidence interval, between meaningfulness and ITT. The correlation coefficient was classified as a moderate effect ($0.3 < r < 0.5$). Furthermore, the relationship between meaningfulness and ITT was classified as monotonic through a visual assessment of the scatter plot (Appendix B, Figure 16). **Therefore, the null for hypothesis three was rejected** at a 5% level of significance and hence it can be concluded that a significant, negative relationship exists between meaningfulness and ITT based on the results of the Spearman's rank order test.

5.7.4 Hypothesis 4

Hypothesis 4 sought to establish if a positive relationship existed between RPA and DE through the following hypothesis:

H₀: There is no relationship between RPA and DE

H₄: There is a positive relationship between RPA and DE

Table 23: Correlation test: RPA and DE

Correlations			
Hypothesis 4		RPA	DE
RPA	Correlation Coefficient	1	-.04
	Sig. (2-tailed)		0.65
	N	120	120

From Table 23 above, the Spearman's rank order test reported a negative correlation coefficient of -0.04, which was **not** significant at the 95% confidence interval, between RPA and DE. The correlation coefficient was classified as a negligible effect ($r < 0.1$). Furthermore, the relationship between RPA and DE was classified as non-monotonic through a visual assessment of the scatter plot (Appendix B, Figure 17). **Therefore, the null for hypothesis four was not rejected** at a 5% level of significance and hence it can be concluded that no relationship exists between RPA and DE based on the results of the Spearman's rank order test.

5.7.5 Hypothesis 5

Hypothesis five sought to establish if a negative relationship existed between RPA and ITT through the following hypothesis:

H₀: There is no relationship between RPA and ITT

H₅: There is a negative relationship between RPA and ITT

Table 24: Correlation test: RPA and ITT

Correlations			
Hypothesis 5		RPA	ITT
RPA	Correlation Coefficient	1	-.23**
	Sig. (2-tailed)		0.01
	N	120	120

From Table 24 above, the Spearman's rank order test reported a negative correlation coefficient of -0.22, which was significant at the 95% confidence interval, between RPA and ITT. The correlation coefficient was classified as a small effect ($0.1 < r < 0.3$). Furthermore, the relationship between RPA and ITT was classified as monotonic through a visual assessment of the scatter plot (Appendix B, Figure 14). **Therefore, the null for hypothesis five was rejected** at a 5% level of significance and hence it can be concluded that a significant, negative relationship exists between RPA and ITT based on the results of the Spearman's rank order test.

5.8 Potential mediation interactions for hypotheses six and seven

The theoretical model developed by the researcher in Section 2.6 of this study proposed a potential mediating interaction by meaningfulness on RPA's relationship between DE and ITT. Hayes Process model four was adopted, as discussed in Section 4.8.2 of this study, to assess the potential mediating interaction via a mediated regression analysis. Relationships between the independent, dependent and potential mediator variable have been assessed via H1 – H5 above and as per the mediation requirements outlined by Baron and Kenny (1986) and Hayes (2009). The results of meaningfulness's potential mediation interaction are presented in hypotheses six and seven that follow.

5.8.1 Hypothesis 6

Using a mediated regression analysis, hypothesis six sought to establish if meaningfulness had a mediating effect on the relationship between RPA and DE through the following hypothesis:

H₀: Meaningfulness does not have a mediating effect on the relationship between RPA and DE

H₆: Meaningfulness has a mediating effect on the relationship between RPA and DE

For a model to be appropriate for a mediation test, the following requirements need to be met as per Baron and Kenny (1986): a significant relationship between RPA

and meaningfulness (tested via H_1), a significant relationship between meaningfulness and DE (tested via H_2) and a significant relationship between the RPA and DE (tested via H_4). As per H_4 in Table 23 above, no relationship existed between RPA and DE, therefore the researcher was unable to evaluate hypothesis six as the requirements for assessing a mediation interaction were not met. **Therefore, the null for H_6 could neither be rejected nor accepted.**

5.8.2 Hypothesis 7

Using a mediated regression analysis, hypothesis seven sought to establish if meaningfulness had a mediating effect on the relationship between RPA and ITT though the following hypothesis:

H_0 : Meaningfulness does not have a mediating effect on the negative relationship between RPA and ITT

H_7 : Meaningfulness has a mediating effect on the negative relationship between RPA and ITT

Table 25: Mediated regression: meaningfulness

OUTCOME VARIABLE						
Meaningfulness						
Model Summary						
R	R-sq	MSE	F	df1	df2	p
0.17	0.28	0.46	3.41	1	118	0.07
Model						
	coeff	se	t	p	LLCI	ULCI
constant	1.53	0.15	10.00	0.00	1.23	1.84
RPA	0.09	0.05	1.85	0.07	-0.01	0.19

Table 26: Mediated regression: ITT

OUTCOME VARIABLE						
ITT						
Model Summary						
R	R-sq	MSE	F	df1	df2	p
0.48	0.23	1.82	17.42	2	117	0.00
Model						
	coeff	se	T	p	LLCI	ULCI
constant	6.89	0.42	16.51	0.00	6.07	7.72
RPA	-0.15	0.1	-1.53	0.13	-0.36	0.05
Meaningfulness	-0.99	0.18	-5.37	0.00	-1.35	-0.62

Table 27: Mediated regression: Total effect model

Total effect model						
ITT						
Model Summary						
R	R-sq	MSE	F	df1	df2	p
0.20	0.04	2.26	4.90	1	118	0.03
Model						
	coeff	se	t	P	LLCI	ULCI
constant	5.38	0.34	15.73	0.00	4.70	6.06
RPA	-0.25	0.11	-2.21	0.03	-0.47	-0.03

As per the mediation assumptions in Section 5.8.1 (H6), all 3 assumptions were met, and the mediation model was suitable for further analysis (H₁, H₃ and H₅ relationships were significant). A regression model was used to assess the statistical significance of meaningfulness as a mediating variable on the relationship between RPA and ITT. Hayes Process model four was used as discussed in Section 4.8.2, the results of which are summarised in Tables 25 – 27. There was a significant indirect effect of RPA on ITT through meaningfulness [RPA on meaningfulness (a) x meaningfulness

on ITT (b)], $a \times b = 0.09$. In addition, meaningfulness accounted for 37% of the total effect in the mediation model (indirect effect / total effect). Furthermore, as seen in Table 27, RPA reported a significant total effect size of -0.25 on ITT. The VAF was calculated at 34% (refer to mediation summary below) indicating a **partial mediating effect** ($20\% < \text{VAF} < 80\%$). **Therefore, the null for hypothesis seven was rejected** at the 5% level of significance and hence it can be concluded that meaningfulness partially mediated the relationship between RPA and ITT.

Mediation summary:

Indirect effect: $a (0.0926) \times b (-0.9852) = 0.0912$

Direct effect: $c (0.1547)$

Total effect: $0.0912 + 0.1547 = 0.2459$ or 0.25 (25%)

VAF: $0.0912 / 0.2459 = 0.3371$ or 0.34 (34%)

Impact of mediator: $0.0912 / 0.2459 = 0.3708$ or 0.37 (37%)

5.8 Conclusion

The purpose of this research was to understand how an emerging technology in the form of RPA, influenced voluntary work outcomes of DE and ITT, that are strongly associated with organisational performance, of knowledge workers. Statistically, this meant testing whether any significant relationships existed between RPA and DE and ITT and testing the extent to which meaningfulness explained these relationships via a mediation model.

Hypothesis 1 to 5 was assessed using the Spearman's rank order test as the data was found to be approximately not normally distributed which was evaluated using the Shapiro-Wilk test for normality. Through the correlational analysis, RPA reported a significant positive relationship with meaningfulness ($r = 0.23, p < 0.05$), no relationship with DE ($r = -0.04, p > 0.05$) and a significant negative relationship with ITT ($r = -0.23, p < 0.05$). Furthermore, meaningfulness reported a significant positive relationship with DE ($r = 0.51, p < 0.05$) and a significant negative relationship with ITT ($r = -0.39, p < 0.05$). Finally, RPA reported a significant indirect effect on ITT

through meaningfulness whereby meaningfulness accounted for 37% of the total effect. The mediating effect was classified as partial since the VAF was calculated at 34% ($20\% < \text{VAF} < 80\%$).

CHAPTER 6: DISCUSSION OF RESULTS

6.1 Introduction

The purpose of this research was to understand how an emerging technology in the form of RPA, influenced voluntary work outcomes of DE and ITT, that are strongly associated with organisational performance, of knowledge workers. Drawing from the research on an antecedent and outcome model of EE developed by Shuck et al. (2011), the researcher proposed that RPA will have a positive relationship with DE and a negative relationship with ITT. Meaningfulness, a dimension of EE (Kahn, 1990), will explain the existence of these relationships via a mediation model. The theoretical model proposed by the researcher in Section 2.3 is developed from an extensive review and discussion of literature in Chapter 2 around meaningfulness, DE, ITT, RPA and knowledge workers. Research hypotheses in Chapter 3, that have been systematically derived from the literature reviewed in Chapter 2, were used to test the proposed relationships that are put forward by the researcher.

The layout of this chapter is ordered in a specific manner. It discusses the results of the statistical tests presented in Chapter 5 that was based on the research methodology articulated in Chapter 4. However, these results are contextualised within the literature reviewed in Chapter 2. The chapter commences with a recap of the salient findings from the literature reviewed in Chapter 2. Thereafter, the RPA scale that was developed for the purposes of this study will be discussed followed by a discourse as to whether the research hypotheses have been met with consideration to sample population.

6.2 Recap of literature review

Knowledge workers are considered organisational value creators (Drucker, 1999) and thrive within jobs that: are dynamic and require a degree of autonomy (Gambardella et al., 2015); are well-designed (May et al., 2004; Oldham & Fried, 2016) and have the correct technology supporting them (Davenport, 2011; Davenport et al., 1996). RPA is an emerging technology that has recently seen increased adoption rates in practice (Agaton & Swedberg, 2018, Lacity et al., 2015).

It is described as a subset of repetitive task automation that uses computer software to execute high-volume, routine or repetitive tasks within a job, that were previously performed by a human, according to business rules (Davenport & Kirby, 2016; Willcocks et al., 2015) and can restructure existing work so that employees can focus on more abstract tasks and greater levels of human interaction (Avasthy, 2019). Work restructuring may enable an employee to organise tasks within their job to maximise skill utilisation and autonomy levels (Bakker & Demerouti, 2004; Petrou et al., 2018; Tim et al., 2016). Knowledge worker tasks can be categorised as routine (easy to automate) and abstract (not easy to automate) (Autor, 2015; Autor & Price, 2013; Davenport, 2011; Davenport & Kirby, 2016) and from a knowledge worker perspective, RPA is designed to complement tasks within their job (Autor, 2015). Depending on the type of work knowledge workers perform, the application of suitable technology will improve their productivity, retention rates (Davenport, 2011) and ultimately, work meaningfulness.

Meaningfulness is defined as significant (Rosso et al., 2010), enriching and positive work (Bailey et al., 2017) that is derived through a process of sensemaking (Aguinis & Glavas, 2019) and is predicted primarily by 4 dimensions: (1) work tasks, (2) work roles, (3) work interaction and (4) organisational attributes (Bailey et al., 2017). Therefore, jobs that have tasks which: are of significance to the employee (Rosso et al., 2010) and have identity that require a variety of skills to execute (Allen et al., 2010; Hackman & Oldham, 1976); are well designed and challenging with a degree of autonomy (Allen et al., 2010; Kahn, 1990; May et al., 2004) are complementary to the employee providing a degree of enrichment (May et al., 2004), are aligned to the employee's value system (Renn & Vandenberg, 1995); enables higher levels of human interaction (Bailey et al., 2017) and provides a sense of belonging, interdependence, value sharing and common purpose (Lips-Wersma & Morris, 2009) will contribute to high levels of work meaningfulness. Organisational systems and culture (Stein et al., 2019) together with person-organisation fit (Resick et al., 2007) are also enablers to work meaningfulness.

The act of deriving meaningfulness from the above stimuli will then commence through a process of sensemaking (Aguinis & Glavas, 2019) where the interplay between intra-individual, intra-organisational and extra-organisation factors deconstruct and codify the stimuli according to a rule-based system of sensemaking that enables an employee to attach an element of meaningfulness to it.

Meaningfulness is the largest predictor of EE (May et al., 2004) and understanding how to achieve high levels of work meaningfulness from employees will contribute to increasing EE levels.

The organisational and individual benefits of EE are widely reported in literature (Harter et al., 2002; Huselid, 1995; Markos & Sridevi, 2010; Rich et al., 2010, Truss et al., 2013). Engaged employees are problem solvers (Richman, 2006) and human resource strategies with a strong EE agenda can result in competitive advantage for an organisation (Albrecht et al., 2015). Strong relationships between EE and organisational and customer value exist (Harter et al., 2002) and employees who experience high engagement levels exert quantifiably more effort and are less likely to leave their organisation (Buchanan, 2004). EE literature shows that engagement is positively related with DE and negatively related with ITT (Saks, 2006; Shuck et al., 2011).

DE has a positive relationship with organisational performance (Brown & Leigh, 1996; Lloyd, 2008) and is enabled primarily by skill variety and autonomy. ITT is negatively related to organisational performance (Allen et al., 2010; Park & Shaw, 2013; Trevor & Nyberg, 2008) and impacts performance directly (rehiring and training costs to replace employees) and indirectly (via tangible and intangible separation costs that disrupts organisational harmonics when key personnel leave) (Allen et al., 2011).

The following salient point are evident from the literature review: (1) the importance of work meaningfulness, what enables it, how it is derived and what are its outcomes, (2) the importance and outcomes of DE and ITT from a personal and organisational perspective and how the voluntary nature of these constructs make them complex to achieve (3) the organisational and personal advantages of RPA as an emerging technology in business and the unknown effect it has on work meaningfulness, DE and ITT amongst (4) knowledge workers who are the key drivers of innovation and success in an organisation.

6.3 Sample descriptive discussion

As discussed in Section 5.2, a valid sample of 120 responses were obtained after screening for eligibility, completion rates and data imputation. About 73% of the

sample was between 25 and 44 years of age with about 20.8% in a specialist role, 19.2% were middle managers and 27.5% were senior managers. 10.8% reported their jobs at an executive level. 86.7% of the respondents were in a possession of a tertiary qualification with 16.7 having a bachelor's degree, 20% having an honours qualification and 30.8% reported being in possession of a master's degree. 2.5% had PhD's and 4.2% were in possession of a professional designation. From a tenure perspective, the 1-5 year and greater than 10 years were tied at 28.3% with 24.2% of the sample were working between 5 and 10 years at their jobs. The finance, mining and telecommunications industries were the most prevalent employers at 25.8%, 25.8% and 23.3% respectively.

The prevalence of RPA exposure is evident from the diverse age groups, job categories, tenures and education levels however, RPA seems to be the most concentrated in finance, mining and telecommunication industries. Interestingly, the high overall tertiary education rate of 86.7% together with the high management concentration implies that there were highly skilled respondents within the sample, especially when one considers that 30.8% of the sample were in possession of a master's degree. When this is looked at in conjunction with knowledge worker job types from Table 7, the 16.7% reported as routine work by this sample is corroborated for accuracy of response, since one would expect this sample to be performing predominantly abstract tasks. This too is corroborated via the reported 52.5% as abstract tasks performed.

6.4 Scale development discussion - RPA

As discussed in Section 4.6, RPA is a new phenomenon with limited academic literature to support it with organisations only recently showing an increase in RPA adoption rates (Agaton & Swedberg, 2018; Willcocks et al., 2015). Due to the limited academic information, a measurement scale was developed following scale development theory (Carpenter, 2018; Churchill, 1979; Hinkin, 1995; Reidenbach & Robin, 1990; Tay & Jebb, 2016; Worthington & Whittaker, 2016) as outlined in Section 4.6.

During the 8-step scale development process devised by Churchill (1979), that was adopted for the purposes of this study, an assessment of reliability was performed in

step 4 (purify the measure) of the of the process. An alpha coefficient of 0.96 was returned together with a contradictory EFA, suggesting multidimensionality as opposed to a unidimensional scale that was initially conceived when the domain was specified in step one (specify domain of the construct). As discussed in Section 4.6, scales with large alpha coefficients (greater than 0.95) may suggest item redundancy (Carpenter, 2018; Chen & Kraus, 2004; Goforth, 2015; Tavakol & Dennick, 2011). Due to time constraints, it was decided to continue with the study with the scale as-is and the researcher attributed the inaccurate reliability and factor indices to the small sample size of the pilot test (n = 15).

Responses from 120 respondents were subsequently received and factor analysis and reliability were reassessed. All items within the scale loaded against one factor (RPA) confirming the unidimensional nature of the scale (refer to Table 14 for further details) however, internal consistency calculations returned the same alpha coefficient of 0.96. The initial list of items generated were assessed for redundancy and the scale was amended as follows:

Table 28: RPA scale adjustment

Item	Final status
Routine or repetitive tasks within my job have been replaced with RPA.	Item remained
RPA enables me to accomplish my overall job objectives more effectively.	Item remained
RPA allows me to spend more time on what I was employed to do.	Item removed
RPA allows me to be more creative and innovative because my routine and repetitive tasks have been replaced by RPA.	Item remained
RPA improves my job performance.	Item removed
RPA improves my job productivity.	Item remained
RPA improves my job effectiveness.	Item remained
RPA makes it easier to do my job.	Item removed
RPA allows me to spend more time on analysis, add value and make better job decisions.	Item removed

4 items from the scale were considered redundant and removed (refer to Appendix C for detailed workings). The remaining items from the scale were assessed for internal consistency and returned an alpha coefficient of 0.89 which was deemed acceptable (Hinkin, 1995).

6.5 Summary of key results: H₁ – H₇ and knowledge worker job types

Table 29: Summary of results: Hypotheses H1 – H7

(*Cor* = Correlation; *IE* – indirect effect)

Hypothesis	Cor/IE	Sig	Result
There is a positive relationship between RPA and meaningfulness	0.23	0.01	Positive, significant relationship exists
There is a positive relationship between meaningfulness and DE	0.51	0.00	Positive, significant relationship exists
There is a negative relationship between meaningfulness and ITT	-0.39	0.00	Negative, significant relationship exists
There is a positive relationship between RPA and DE	-0.04	0.65	No significant relationship exists
There is a negative relationship between RPA and ITT	-0.23	0.01	Negative, significant relationship exists
Meaningfulness has a mediating effect on the relationship between RPA and DE	Could not assess mediating effect. No significant relationship between RPA and DE		
Meaningfulness has a mediating effect on the negative relationship between RPA and ITT	0.09	0.03	Partial mediation exists. VAF = 34% (20% < VAF < 80%)

Table 30: Recap: Knowledge work job types

Task Type	Sample Response	
Routine Tasks (Easily Automatable)	20 (16,7%)	37 (30,8%)
Abstract Tasks (Not easily Automatable)	63 (52,5%)	

As discussed in Section 2.2.2, Figure 1 split knowledge work types into 4 quadrants based on whether it was routine, repeatable, improvisational or judgement-oriented (Davenport, 2011). It also categorised work according to whether it can be performed individually or requires collaboration. The researcher triangulated literature and was able to cluster these 4 quadrants into routine tasks (easy to automate) and abstract tasks (not easy to automate) (Autor, 2015; Autor & Price, 2013; Davenport, 2011). The sample of 120 were respondents, who had tasks within their jobs impacted by RPA, were requested to select attributes that best described their current daily work. As per Table 30 above, 20 (16.7%) reported their work as being routine, 63 (52.5%) reported their work as being abstract and 37 (30.8%) knowledge workers reported their work as being a mixture of routine and abstract tasks which supports the view that work is a combination of routine and complex tasks (Autor, 2015; Mendling et al., 2018).

6.5.1 Hypothesis 1: There is a positive relationship between RPA and meaningfulness

Based on the literature reviewed in Chapter 2, the researcher put forward that RPA will have a positive relationship with meaningfulness and the research objective for this hypothesis **has been met**. Results reported in Section 5.7.1 and summarised in Table 29 indicated that RPA has a statistically significant, positive relationship with meaningfulness ($r = 0.23$, $p < 0.05$ at the 95% confidence interval). The correlation

effect of 0.23 was categorised as a small effect ($0.1 < r < 0.3$). The mean score for meaningfulness of $m = 1.80$ for the research sample implies that they view their current work as highly meaningful. The mean score for RPA of $m = 2.82$ suggests that RPA does assist in improving their current jobs implying that benefit is being derived from the technology. There evidence in the literature to support this assertion is as follows.

Literature asserts that meaningfulness is predicted by the following domains: (1) work tasks, (2) work roles, (3) work interaction and (4) organisational attributes (Bailey et al., 2017) including significance (Rosso et al., 2010) as per the operational definition of meaningfulness. Therefore, work which is well designed, enabling creativity (Kahn, 1990), challenging and provides a degree of autonomy (May et al., 2004), enables one use of a variety of skills (Hackman and Oldham, 1976; Renn and Vandenberg, 1995) and impactful and therefore significant (Hackman & Oldham, 1976; Rosso et al., 2010) contributes to work meaningfulness (Bailey et al., 2017). Work is usually a combination of tasks (Mendling et al., 2018) and RPA's ability to replace routine tasks that were previously performed by a human (Autor, 2015; Davenport & Kirby, 2016; Lacity & Willcocks, 2015; Lacity & Willcocks, 2016; Lacity, Willcocks, & Craig, 2015; Willcocks et al., 2015) and restructure existing work so that emphasis is placed on abstract tasks (Avasthy, 2019) will contribute to enhancing the meaningfulness domains as follows:

Work tasks

By replacing routine tasks, skill utilisation for abstract tasks may improve as a result of increased levels of focus on these tasks. This contributes to more challenging work being performed and increased levels of creativity. Work requirements may become clearer as skilled knowledge workers are able to apply themselves better at abstract work. Autonomy enhances the task characteristics of knowledge workers (Gambardella et al., 2015; May et al., 2004) and RPA may be able to produce data that is required for decision making to progress to advanced work stages at a faster rate, thereby supporting and improving the autonomy levels a knowledge worker needs to have in the execution of their tasks. However, this autonomy is limited in powers to what has been granted my management and HRD in arriving at a job specification. Therefore, knowledge workers can merely rearrange tasks within their

jobs, within an RPA context, to improve autonomy levels to the extent that the job specification allows (Petrou et al., 2018; Tim et al., 2016),

Work roles

Work roles that are aligned to one's favoured self-image contribute to work meaningfulness (Kahn, 1990) including the perception of one's work by others as being high in stature (Bailey et al., 2017). Fit theory (Resick et al., 2007) posit that congruence between personal and job characteristics that improves person-job or work role fit will contribute to meaningful work and studies proved that work role fit predicted meaningfulness (May et al., 2004). RPA's ability to restructure existing work by replacing routine tasks enables a knowledge worker to focus on abstract tasks. The high skill utilisation while performing abstract tasks will improve preferred self-image, the way the knowledge worker and their work is perceived and ultimately enhance work meaningfulness. Improved self-image and perception by others on how impactful work is enhances significance (Hackman & Oldham, 1976; Rosso et al., 2010).

Work interactions

Work interactions is a contributor to meaningfulness (Bailey et al., 2017) where there is an inherent need to be connected through work and a sense of belonging, interdependence and value sharing creates bonds that articulate a common purpose (Lips-Wiersma & Morris, 2009). One of the core tenants of RPA is the improved levels of human interaction due extra time being available since routine tasks have been replaced and the increased focus on abstract tasks requiring more cross-functional collaboration (Avasthy, 2019; Davenport & Kirby, 2016; Lacity & Willcocks, 2016; Willcocks et al., 2015). Therefore, introducing RPA may improve work interactions and enhance meaningfulness.

Organisational attributes

Meaningful work relies organisational systems to support it (Stein et al., 2019) where institutionalised norms, embedded culture and organisation-employee fit contribute

to meaningfulness (Bailey et al., 2017). Fit theory (Resick et al., 2007) will help explain this organisational element of meaningfulness. One of the ways fit is improved occurs when the employee can provide the organisation with what the organisation requires *or vice-versa*, promotes fit. RPA's ability to allow an employee to focus on abstract work that's value adding and beneficial to the organisation, given a knowledge workers role in organisational success (Drucker, 1999), will contribute to person-organisation fit and ultimately work meaningfulness. Deeper elements of organisational culture and how a digital transformation agenda with RPA as one of its enablers, was not within the scope of this study.

As per the above discussion, evidence exists in literature regarding RPA's contribution to the meaning of work, and this supports the positive, significant relationship between RPA and meaningfulness of H₁, however, the strength of the relationship between RPA and meaningfulness (0.23) implies that even though RPA contributes to improving work (mean = 2.82) it does not impact meaningfulness strongly as per the small correlation effect, given that the sample already experiences high levels of meaningfulness in their work (mean = 1.80). This may be attributed to the type of work that the knowledge worker sample performs. Table 30 suggests that only 16.7% of respondents within the sample perform routine work that fully supports an RPA agenda in its entirety and 30.8% of the sample perform work that is a mixture of routine and abstract tasks. 52.5% of respondents perform work that is totally of an abstract nature and is not easily automatable.

Given that this entire sample has been impacted by RPA within their jobs, the weak correlation effect of 0.23 between RPA and meaningfulness may be indicative of the sub-optimal allocation of RPA across different work types and RPA is being applied to job types that may not benefit from it. RPA may be improving meaningfulness of work, but only to the extent that work is conducive to the technology. In sum, the weak correlation between RPA and meaningfulness and the high meaningfulness mean imply that the sample finds its work meaningful, however not all this meaning is derived from RPA. However, the underlying implication of this research objective being met is that the principles of RPA have a significant positive relationship to the meaningfulness of work, however, to fully exploit its capabilities, RPA needs to be positioned across job types which support and complement its abilities.

6.5.2 Hypothesis 2: There is a positive relationship between meaningfulness and DE

Based on the literature reviewed in Chapter 2, the researcher put forward that meaningfulness will have a positive relationship with DE and the research objective for this hypothesis **has been met**. Results reported in Section 5.7.2 and summarised in Table 29 indicated that meaningfulness has a statistically significant, positive relationship with DE ($r = 0.51$, $p < 0.05$ at the 95% confidence interval). The correlation effect of 0.51 was categorised as a large effect ($r > 0.5$) and the reported means for meaningfulness $m = 1.80$ and DE $m = 1.84$ imply that the sample experiences high levels of meaningfulness from their work and exert high levels of effort in executing their work. There is evidence in the literature to support this assertion is as follows.

Meaningfulness is a predictor of improved work performance (Hackman & Oldham, 1976; Kahn, 1990; Renn & Vandenberg, 1995) and is the largest contributor to EE (May et al., 2004) which has a direct relationship with DE levels (Saks, 2006; Shuck et al., 2011) since engaged employees exert 57% more effort into their work (Buchanan, 2004). The primary drivers of DE have been reported as skill variety and autonomy (Lloyd, 2008) which are congruent with that of meaningfulness as meaningful work is described as challenging and well-designed that provides a level of autonomy (Kahn, 1990; May et al., 2004). Therefore, the existence of a strong significant relationship between meaningfulness and DE has been corroborated by the knowledge worker sample within this study. As per Table 30, 52.5% of this sample have reported that their work is of an abstract nature. Given the sample descriptive suggesting highly qualified knowledge workers with a bias toward management positions, autonomy and skill variety may be present thus securing high levels of meaningfulness (mean = 1.80) and high levels of DE (mean = 1.84).

6.5.3 Hypothesis 3: There is a negative relationship between meaningfulness and ITT

Based on the literature reviewed in Chapter 2, the researcher put forward that meaningfulness will have a negative relationship with ITT and the research objective for this hypothesis **has been met**. Results reported in Section 5.7.3 and summarised in table 29 indicated that meaningfulness has a statistically significant, negative

relationship with ITT ($r = -0.39$, $p < 0.05$ at the 95% confidence interval). The correlation effect of -0.39 was categorised as a moderate effect ($0.3 < r < 0.5$) and the reported means for meaningfulness $m = 1.80$ and ITT $m = 4.69$ imply that the sample experiences high levels of meaningfulness from their work and have a low ITT. There is evidence in the literature to support this assertion is as follows.

Meaningfulness is a predictor of improved work performance while improving work attendance and reducing staff turnover levels (Hackman & Oldham, 1976; Kahn, 1990; Renn & Vandenberg, 1995) and is the largest contributor to EE (May et al., 2004) which has a negative relationship with ITT (Saks, 2006; Shuck et al., 2011) since engaged employees 87% less likely to leave their jobs (Buchanan, 2004). Meaningful work is clearly delineated, well designed, challenging and provides a level of autonomy (Kahn, 1990; May et al., 2004) and these attributes are key predictors of ITT (Allen et al., 2010; Hackman & Oldham, 1976; Kahn, 1990; Mitchell et al., 2001). Therefore, the existence of a moderate and significant negative relationship between meaningfulness and ITT has been corroborated by the knowledge sample within this study. As per Table 30, 52.5% of this sample have reported that their work is of an abstract nature. Given the sample descriptive suggesting highly qualified knowledge workers with a bias toward management positions, autonomy and skill variety may be present thus securing high levels of meaningfulness (mean = 1.80) and low levels of ITT (mean = 4.69).

6.5.4 Hypothesis 4: There is a positive relationship between RPA and DE

Based on the literature reviewed in Chapter 2, the researcher put forward that RPA will have a positive relationship with DE and the research objective for this hypothesis **has not been met**. Results reported in Section 5.7.4 and summarised in table 29 indicated that RPA has a statistically insignificant, negative relationship with DE ($r = -0.04$, $p > 0.05$ at the 95% confidence interval). The correlation effect of -0.04 was categorised as negligible ($r < 0.1$). DE reported a mean score of $m = 1.84$ which implies that the sample population exerts high levels of effort in the execution of their work. RPA reported a mean of $m = 2.82$ implying a level of benefit being derived from the technology. However, the literature regarding DE needs closer analysis to explain this contradictory finding of the non-significant relationship between DE and RPA, commencing with a reiteration of what DE means.

DE is defined as the exerted effort that exceeds the agreed upon minimum as contractually agreed between employer and employee (Frenkel & Bednell, 2016). Therefore, the quantum of extra effort is a function of one's discretion and hence is behaviour of a voluntary nature. The predictors of DE have been described as skill variety and autonomy (Lloyd, 2008) and psychological climate (Shuck et al., 2011). From a skill variety and autonomy perspective (Lloyd, 2008), autonomy emerged as a stronger predictor of DE than skill variety. Therefore, in the context of this study, the extent to which RPA enhances one's skill usage in the execution of tasks together with the level of autonomy that's derived will determine the level of effort one will exert according to Lloyd's (2008) conceptualisation. Knowledge workers within this sample already exert high levels of DE that is evident from the strong mean of 1.82 reported however, this effort is not as a result of RPA, since no relationship between DE and RPA exists.

Knowledge workers require a degree of autonomy for the effective and efficient delivery of output (Gambardella et al., 2015) and as discussed in Section 6.5.1 (H₁), the level of autonomy that RPA offers is limited in powers to what has been granted my management and HRD in arriving at a job specification. Therefore, knowledge workers can merely rearrange tasks within their jobs, within an RPA context, to improve autonomy levels to the extent that the job specification allows (Petrou et al., 2018; Tim et al., 2016). As such, it is the design of the job that defines its decision-making powers which either enhances or restrains autonomy. Job design is beyond the control of the employee (Tim et al., 2016) and job redesign will require management and HRD intervention to properly realise improved autonomy as a result of RPA. Therefore, from an autonomy perspective, the introduction of RPA into a job will not provide the autonomy levels required to enhance DE up until such time a formal redesign of the job is undertaken by management and HRD.

From a skill variety perspective, and as discussed in Section 6.5.1, by replacing routine tasks, skill utilisation for abstract tasks may improve as a result of increased levels of focus on these tasks. This contributes to more challenging work being performed and increased levels of creativity. Work requirements may become clearer as skilled knowledge workers will be able to apply themselves better at abstract work. The question that arises is whether the extent to which RPA replaces routine tasks is substantial enough such that the skill set of the employee is fully exploited such that extra effort, above the contractually agreed amount (Frenkel & Bednell, 2016) is

exerted? Given the result of the research hypothesis, the answer is probably no, and just as job redesign efforts may be required to secure higher levels of effort from an autonomy perspective, so does skill variety to ensure that skills are effectively utilised leading to higher effort levels. Therefore, skill variety within an RPA context may be realised to the extent that it contributes to meaningfulness (as per H_1 in Section 6.5.1) but not to the extent that extra effort is exerted.

The psychological climate dimensions of supportive management, challenge and contribution (Brown & Leigh, 2004) were the contradictory predictors of DE in Shuck's et al. (2011) study of EE. The initial hypothesis within this study (Shuck et al., 2011) was that EE (meaningfulness, safety and availability (Kahn, 1990)) will predict variances in DE and none of the EE dimension did. However, examination of the psychological climate measurement scales used in this study suggested that psychological climate may be underpinned from an autonomy and skill variety perspective (refer to Section 2.4 for further detail). Therefore, one can assume with a reasonable level of assurance that, the primary drivers of DE are autonomy and skill variety. Given that autonomy contributes more to DE than skill variety (Lloyd, 2008), and to derive increased levels of autonomy will require management and HRD intervention, even though RPA may improve skill variety and autonomy to an extent, it is unable to do so without the intervention of management and HRD.

Furthermore, Table 30 provides a summary of the tasks performed by the knowledge worker sample. At 52.5% (including a portion of the 30.8% that reported a mixture of abstract and routine tasks), most of the respondents in this study, whose jobs are impacted by RPA, reported their jobs as abstract (not easy to automate) and as such, would not benefit from RPA. This sample may benefit more from other types of technology like free-access approaches as described by Davenport (2011). Therefore, effort levels exerted by this sample (DE mean = 1.84) is not as a result of RPA and probably originate from autonomy and skill usage already present in their jobs since the sample descriptive described in Section 6.3 suggest a bias toward highly qualified, management level staff. However, for the 16.7% of the sample, including a portion of the 30.8% that reported a mixture of abstract and routine tasks, the difficulty in deriving appropriate levels of autonomy and skill variety (as described above) may be impeding effort levels from being realised through RPA application. However, it may have been this segment of the sample that has limited benefit from

RPA in their jobs which may explain the mean score of RPA ($m = 2.82$) indicating benefit from the technology.

An alternative view may be that the jobs of this sample are becoming easier to perform as a result of RPA, given the RPA mean of 2.82, however, given the voluntary nature of DE, no reason may exist to exert more effort given that employee rewards (salaries and benefits) remain unchanged. Notwithstanding the above, the implication of this research objective not being met, within the context of this sample, is that the principles of RPA does not have any impact on DE levels irrespective of the type of job performed. Furthermore, if the job type supports an RPA agenda, then management and HRD intervention may be required via job redesign initiatives to secure improved levels of skill utilisation and autonomy.

6.5.5 Hypothesis 5: There is a negative relationship between RPA and ITT

Based on the literature reviewed in Chapter 2, the researcher put forward that RPA will have a negative relationship with ITT and the research objective for this hypothesis **has been met**. Results reported in Section 5.7.5 and summarised in Table 29 indicated that RPA has a statistically significant, negative relationship with ITT ($r = -0.23$, $p < 0.05$ at the 95% confidence interval). The correlation effect of -0.22 was categorised as a small effect ($0.1 < r < 0.3$). The reported mean of $m = 4.69$ for ITT implies that the sample of knowledge workers within this study have a low ITT or leave the employ of their organisations while deriving some benefit from RPA with a reported mean score of $m = 2.82$. There is evidence in the literature to support this assertion is as follows.

Like the principles of DE, ITT is also a voluntary action whereby an employee voluntarily departs from the organisation (Saks, 2006) when an organisation would generally want to retain such an employee (Allen et al., 2010). EE levels proved to be an important indicator to one's turnover intention (Bakker & Demerouti, 2014; Saks, 2006; Schaufeli & Bakker, 2004; Shuck et al., 2011) and high levels of engagement results in an 87% less likelihood of employees wanting to leave their organisation (Buchanan, 2004). Meaningfulness, the largest predictor of EE (May et al., 2004) is also a key predictor of and negatively related to ITT (Shuck et al., 2011). A significant, positive relationship between RPA and meaningfulness has already

been established in H_1 (refer to Section 6.5.1) so it stands to reason that from an ITT perspective, a negative relationship between RPA and ITT will exist by virtue of the relationship between meaningfulness, EE and ITT (May et al., 2004, Shuck et al., 2011).

Job and task related attributes being the key predictors of ITT are strongly evident in literature (Allen et al., 2010; Hackman & Oldham, 1976; Kahn, 1990; Mitchell et al., 2001). Role clarity was the most important job attribute that can be used to reduce turnover intention since well-designed jobs that contribute to autonomy, skill variety and meaningfulness will result in lower intentions to turnover (Allen et al., 2010). As discussed in H_1 (refer to Section 6.5.1) and H_2 (refer to Section 6.5.2), RPA's work restructuring principles (Avasthy, 2019, Davenport & Kirby, 2016; Lacity & Willcocks, 2016; Willcocks et al., 2015) that enhances role clarity, enables better skill utilisation and improved levels of autonomy, within the confines of a given job specification, will contribute to reducing turnover intention levels. This is evident in the results of this hypothesis.

However, the negative and significant relationship between RPA and ITT needs to be understood and contextualised within the contradictory findings of H_2 , the non-significant relationship between RPA and DE. H_2 reported that no relationship exists between RPA and DE. The postulation by the researcher for this finding is that in the absence of job redesign, RPA does not improve autonomy and skill utilisation to the extent that extra effort is exerted. This is further aggravated by the job types of the knowledge worker sample and their suitability to RPA.

Within the context of this hypothesis (H_3), the key question that arises is whether RPA responsible for the low ITT (ITT mean = 4.69)? The small correlation effect of -0.22 could imply that the reasons in not wanting to turnover may be partially attributable to the existence of RPA and, as per Table 30, may only relate to the 16.7% and a portion of the 30.8% of the sample population. Employees may already be experiencing high levels of skill variety and autonomy given that 52.5% of the sample population perform abstract tasks not suited to an RPA agenda.

Alternatively, this observation together with the lack of RPA – DE relationship (see Section 6.5.4 H_4) could imply that jobs may have become easier to perform by virtue of RPA without displaying the corresponding increase in effort levels (as assumed in 6.5.4). Employees performing jobs that are easier will be more incentivised to stay

given that their rewards (salaries and benefits) remain unchanged. Notwithstanding the above, the theoretical implication of this research objective being met is that the principles of RPA have a significant and negative relationship with ITT.

6.5.6 Hypothesis 6: Meaningfulness has a mediating effect on the relationship between RPA and DE

Based on the literature reviewed in Chapter 2, the researcher put forward that meaningfulness will mediate the relationship between RPA and DE and the research objective for this hypothesis **could not be assessed**. Results reported in Section 5.7.6 and summarised in Table 29 indicated that the conditions for a mediation test was not met.

For a model to be appropriate for a mediation test, the following requirements need to be met as per Baron and Kenny (1986): a significant relationship between RPA and meaningfulness which was tested via H_1 (refer to Section 6.5.1), a significant relationship between meaningfulness and DE which was tested via H_2 (refer to Section 6.5.2) and a significant direct effect between RPA and the DE which was tested via H_4 (refer to Section 6.5.4). As discussed in Section 6.5.4 no statistically significant relationship between RPA and DE existed.

Therefore, one of the conditions of mediation was not fulfilled (Baron & Kenny, 1986; Preacher & Hayes, 2004) and a mediation assessment could not be performed since a mediation interaction will only hold true if a significant relationship was initially established between RPA and meaningfulness. Based on the above, the null hypothesis could neither be rejected nor accepted.

6.5.7 Hypothesis 7: Meaningfulness has a mediating effect on the relationship between RPA and ITT

Based on the literature reviewed in Chapter 2, the researcher put forward that meaningfulness will mediate the relationship between RPA and ITT and the research objective for this hypothesis **has been partially met**. This research has reported the following findings: (1) RPA has a significant negative relationship with ITT (refer to H_5 , Section 5.7.5), (2) meaningfulness has a significant negative relationship with

ITT (refer to H₅, Section 5.7.5) and (3) RPA has a significant relationship with meaningfulness (refer to H₁, Section 5.7.1). Therefore, the mediation assumptions have been met (Baron & Kenny, 1986). The mediated regression analysis has reported a significant mediation effect of meaningfulness on the relationship between RPA and ITT with a significant negative indirect effect of 0.09 (refer to Table 25 – Table 27). Furthermore, as discussed in Section 4.8.2, the Preacher and Hayes (2008) method of product coefficients of the betas that was used to calculate the mediating effect from the mediated regression analysis reported a partial indirect mediating effect of meaningfulness on the relationship between RPA and ITT resulting in a significant total effect of 0.25 and a VAF of 34%. The following graphically represents the relationship:

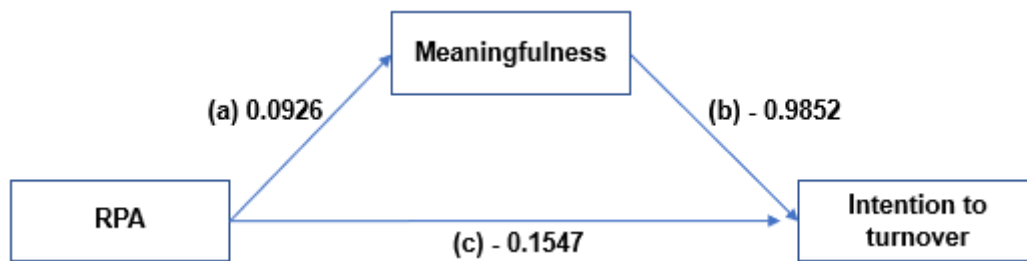


Figure 10: Partial mediation model

Mediation summary calculations

Indirect effect: $a (0.0926) \times b (0.9852) = 0.0912$

Direct effect: $c (0.1547)$

Total effect: $0.0912 + 0.1547 = 0.2459$ or $0.25 (25\%)$

VAF: $0.0912 + 0.2459 = 0.3371$ or $0.34 (34\%)$

Impact of mediator: $0.0912 / 0.2459 = 0.3708$ or $0.37 (37\%)$

The above model is representative of a simple mediation model since only one mediating variable is present in explaining the relationship between RPA and ITT (Preacher & Hayes, 2008). The VAF of 34% implies the existence of a partial indirect

mediation interaction by meaningfulness on the relationship between RPA and ITT ($20\% < \text{VAF} < 80\%$). This means that only 34% of the relationship between RPA and ITT can be explained by the indirect mediating effect of meaningfulness. The remaining direct path represents the unexplained relationship between RPA and ITT (Zhao, Lynch, & Chen, 2010) and may provide evidence to other mediating factors that may have been omitted from the mediation model (Baron & Kenny, 1986; Zhao et al., 2010).

The indirect effect between RPA and ITT that is partially mediated by meaningfulness corroborates Hom's et al. (2012) assertion of choice between an intent and action, which are hallmarks of a voluntary action such as ITT. The choice that exists in the space between intent and action is influenced by the intervening or mediating variable, and in the context of this research, the extent to which meaningfulness can be derived from the work that RPA has restructured (Autor, 2015; Avasthy, 2019; Davenport & Kirby, 2016; Lacity & Willcocks, 2015; Lacity & Willcocks, 2016; Lacity, Willcocks, & Craig, 2015; Willcocks et al., 2015) will determine the choice of whether to act on the intent to turnover or not.

Meaningfulness's role as a mediating variable, either on its own or indirectly via EE, is evident in literature (Hackman & Oldham, 1976; May et al., 2004; Renn & Vandenberg, 1995) and helps to explain why relationships exist between independent and dependent variables. This research has already established a significant relationship between RPA and ITT (refer to H₅, 5.7.5). However, the partial mediation by meaningfulness explains, in part, why this relationship exists. It exists because RPA's restructuring of work has enabled intra-individual, intra-organisational and extra-organisational factors within the sensemaking process described in Figure 2 (Aguinis & Glavas, 2019) to be realised. For example, work orientation (whether one is driven by monetary rewards, career advancement or societal and organisational contribution) within the intra-individual sensemaking factor has been clearly defined as a result of RPA's impact on work. It could be said that due to work becoming more aligned to one's skill sets (because routine tasks have been automated), there is a greater perception by the employee that work is more significant (Rosso et al., 2010) thereby making a greater overall contribution and ultimately enhancing the meaningfulness of work. In this instance, the work orientation of the knowledge worker will be contribution (Aguinis & Glavas, 2019). Similarly, work restructuring through RPA may provide an employee with more family

time, striking an optimal work-life balance within the extra-organisational sensemaking factor resulting in improved meaningfulness (Aguinis & Glavas, 2019) and as such, higher levels of meaningfulness will result in lower intentions to turnover.

Possible reasons for the partial mediating effect of meaningfulness

The mediation effect of meaningfulness described above explains only 34% of the relationship between RPA and ITT and multiple mediators may exist to explain the balance of the relationship (Baron & Kenny, 1986; Zhao et al., 2010). Furthermore, the sample consisted of knowledge workers who were exposed to all types of job types (refer to Table 30), from routine work that is easy to automate to abstract work which is difficult to automate (Autor, 2015; Davenport, 2011). 52.5% of this sample reported jobs of an abstract nature while 16.7% of the sample reported routine jobs while 30.8% reported a mixture of routine and abstract. This knowledge worker sample who are exposed to a diversity of job types may have different interveners between their intentions and actions which may influence their choices differently than just meaningfulness since the degree to which RPA changed the job of a knowledge worker performing abstract tasks may be different to the way it impacts a knowledge worker performing routine tasks. This was explained in greater detail in H₄ (Section 6.5.4), where the absence of a relationship between RPA and DE contradicted the research hypothesis.

As described in H₁ (refer to Section 6.5.1), H₃ (refer to Section 6.5.3) and H₄ (refer to Section 6.5.4), the degree to which RPA can influence skill variety, autonomy and effort levels are limited to the boundaries of the given job specification (Tim et al., 2016) and this may have constrained the mediating effect of meaningfulness on the relationship between RPA and ITT. RPA does not permit an employee to substantially alter characteristics such as autonomy and skill utilisation, attributes which contribute the overall meaningfulness of work (May et al., 2004) to the same extent as job redesign will (Tim et al., 2016). Consequently, with meaningfulness being a constrained explainer, other mediators may have to augment the explanation of this relationship. However, what will be the most viable way to understand and identify these additional mediator variables?

In one study, EE proved to be a better explainer than job satisfaction in the relationship between organisational support and employee performance (Rich et al., 2010) and explained the relationship that existed between job resources and ITT in another study (Schaufeli & Bakker, 2004). Meaningfulness is a dimension of EE together with availability and safety (Kahn, 1990; May et al., 2004). Therefore, the most prudent approach would be to test the mediating effects of the remaining job dimensions of EE to understand if they would, together with meaningfulness, collectively explain the relationship between RPA and ITT, should they meet the requirements for mediation. Refer to Section 2.3.3 for a description of availability and safety.

6.6 Conclusion

The primary objective of this research was to establish how and emerging technology like RPA, that is being adopted by businesses at a rapid pace, impacts organisational performance through an employee's DE and ITT levels. The discussion provided above contextualises the implications of the results and hypothesis from Chapter 5 and 3 respectively that was used to assess this primary research objective. The insights derived from this discussion together with its implications for theory and practice are discussed in the following and final chapter.

CHAPTER 7: CONCLUSION

7.1 Introduction

The purpose of this research was to understand how an emerging technology in the form of RPA, influenced voluntary work outcomes of DE and ITT, that are strongly associated with organisational performance, of knowledge workers. This study provided insights into RPA's impact on the key outcomes of EE that have direct impacts with organisational performance (Allen et al., 2010; Brown & Leigh, 1996; Lloyd, 2008; Park & Shaw, 2013; Trevor & Nyberg, 2008).

At its core, RPA is designed to replace routine tasks that were previously performed by a human within a job (Autor, 2015; Davenport & Kirby, 2016; Lacity & Willcocks, 2015; Lacity & Willcocks, 2016; Lacity, Willcocks, & Craig, 2015; Willcocks et al., 2015) together with restructuring existing work so that employees can focus on abstract tasks that require greater levels of human interaction (Avasthy, 2019). RPA is an emerging technology that has limited academic literature to support it however, the use of RPA in business is increasing year on year (Agaton & Swedberg, 2018; Lacity et al., 2015).

As such, understanding the theoretical relationship of RPA with other well-established theoretical constructs that drive organisational performance and employee retention is important. The following are the salient outcomes of RPA's interplay with meaningfulness, DE and ITT. However, the relationships between meaningfulness and DE and ITT are not considered as principal findings as these relationships existed prior to this study. These relationships will consequently not be discussed in this section.

This chapter consolidates the statistical results from Chapter 5 and detailed discussions of these results from 6 and distils them into principal theoretical findings. The proposed conceptual framework from Section 2.6 is revisited and adjusted according to these findings and implications of the mediation model is discussed together with providing comprehensive implications for management and practice. The limitations of this study outlined and finally, based on these principal findings, suggestions for future research are proposed.

7.2 Principal findings

Direct relationships

Findings from this study support the **positive relationship between RPA and meaningfulness** via the meaningfulness domains suggested by Bailey et al. (2017), particularly enhancing work tasks, work roles and work interactions. Replacing routine tasks within jobs (Autor, 2015; Davenport & Kirby, 2016; Lacity & Willcocks, 2015; Lacity & Willcocks, 2016; Lacity, Willcocks, & Craig, 2015; Willcocks et al., 2015) results in more time and effort being available for abstract tasks. A focus on abstract tasks allows greater skill utilisation, improve autonomy levels and improve interaction with others on abstract tasks that may require cross-functional collaboration (Avasthy, 2019). However, the extent to which RPA can improve autonomy and skill variety is limited to the dimensions of the existing job (Bakker & Demerouti, 2014; Petrou et al., 2018; Tim et al., 2016). Therefore, the findings from this hypothesis contribute to EE literature via the meaningfulness dimension.

DE is an outcome of EE (Macey & Schneider, 2008; Saks, 2006; Shuck et al., 2011; Shuck & Wollard, 2010) and has a direct relationship with organisational performance (Brown & Leigh, 1996; Lloyd, 2008). With DE being influenced primarily by autonomy and skill variety, findings from this study assert that **RPA has no influence on DE levels**. Autonomy has a higher impact on DE levels than skill variety (Lloyd, 2008) and autonomy is a key requirement for knowledge worker effectiveness and efficiency (Gambardella et al., 2015). The degree to which RPA influences autonomy levels and skill utilisation may provide insights into the absence of the relationship between RPA and DE. As discussed above, the extent to which RPA can improve autonomy and skill variety is limited to the dimensions of the existing job (Bakker & Demerouti, 2014; Petrou et al., 2018; Tim et al., 2016). In other words, an employee is unable to improve skill utilisation and autonomy beyond the scope of the job specification and intervention by management and HRD is required in to redesign jobs within the context of RPA such that autonomy is increased, and the degree of skill utilisation is enhanced. Furthermore, as per Table 30, 52.5% and a portion of 30.8% of the sample population reported doing abstract tasks that are difficult to automate. Given that abstract tasks are not suited for RPA, the application to this proportion of the population may be sub-optimal. The findings from this hypothesis contributes directly to DE literature within EE and indirectly to literature

on autonomy, skill utilisation and job redesign via job crafting and JD-R (Bakker & Demerouti, 2014; Petrou et al., 2018; Tim et al., 2016).

There is evidence in this study to support the **significant negative relationship between RPA and ITT**. This research finding contributes to turnover literature from the job characteristics perspective, specifically task significance, task identity, role clarity and work meaningfulness (Allen et al., 2011; Hackman & Oldham, 1976; May et al., 2004; Shuck et al., 2011). However, as discussed above, RPA supports the enablers to ITT, particularly autonomy and skill variety only to the extent that the job specification allows, and any subsequent improvements to autonomy and skill variety beyond this job specification will require job redesign to be initiated from a management and HRD perspective (Bakker & Demerouti, 2014; Petrou et al., 2018; Tim et al., 2016). Notwithstanding the above, one can deduce that the effective use of RPA within the jobs of knowledge workers will reduce their ITT.

Non-principal findings and theoretical model revision

There is evidence in the study to support the significant positive relationship between meaningfulness and DE (refer to Section 6.5.2 for H₂) and there is evidence in this study to support the significant negative relationship between meaningfulness and ITT (refer to Section 6.5.3 for H₃.) Therefore, given these principal and non-principal findings regarding discussed above, the theoretical model initially hypothesised by the researcher in Section 2.6 can be represented as follows:

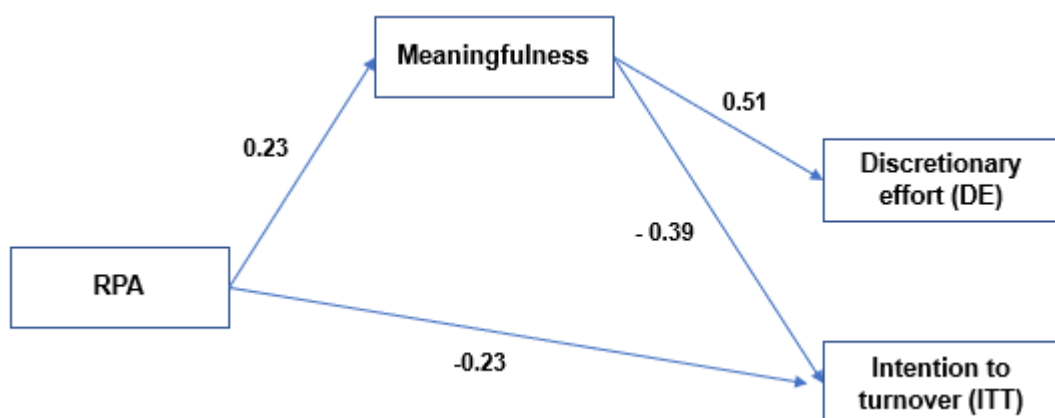


Figure 11: Conceptual framework: RPA's impact on meaningfulness, DE and ITT

Mediated relationships

This study reported no relationship between RPA and DE as per H₄ (refer to Section 5.7.4 and 6.5.4) and as a result, one of the key assumptions for a mediation test was not met (Baron & Kenny, 1986; Preacher & Hayes, 2004). Therefore, H₆'s proposition of meaningfulness potentially mediating the relationship between RPA and DE could not be tested. As a result, no theoretical findings from this test exist, apart from no relationship existing between RPA and DE (refer to direct relationships above).

Meaningfulness however **partially mediated the relationship between RPA and ITT** (refer to Section 6.5.7), the result of which is graphically represented below:

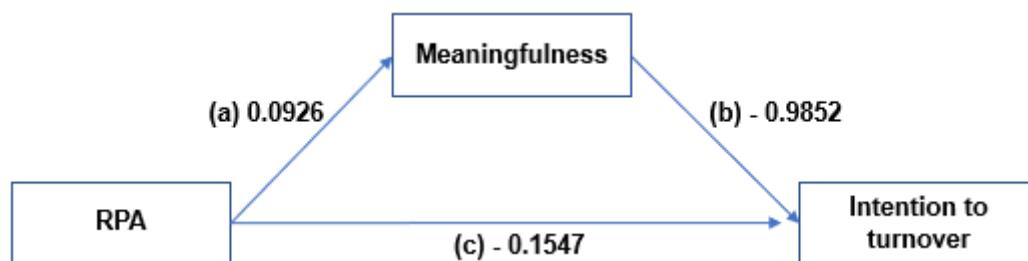


Figure 12: Meaningfulness mediating the relationship between RPA and ITT

Within the context of this study, the partial mediation by meaningfulness on the relationship between RPA and ITT implies that 34% of this relationship can be explained by meaningfulness (refer to Section 6.5.7 for detailed calculations). Therefore, other dimensions, for example availability and safety (Kahn, 1990) may be able to explain why the balance of the relationship between RPA and ITT exists. This finding contributes to EE literature since RPA is tested within a reported dimension of EE (Kahn, 1990; May et al., 2004) together with a reported outcome of EE (Saks, 2006; Shuck et al., 2011).

In sum, principal and non-principal findings of this study, based on the direct and mediated relationships discussed above, can be summarised as follows:

- (1) RPA has a significant positive relationship with meaningfulness,
- (2) RPA has a significant negative relationship with ITT,
- (3) RPA has no relationship with DE,
- (4) Meaningfulness partially mediates the relationship between RPA and ITT,

- (5) The type of work performed by a knowledge worker will determine the success rates of an RPA application to a task set.
- (6) Meaningfulness has a significant positive relationship with DE and a significant negative relationship with ITT (not a principal finding as this relationship has been proved previously),
- (7) RPA may only improve autonomy and skill utilisation levels to the extent that the job specification allows. Any increase in autonomy and skill utilisation beyond this point may require job redesign and subsequent management and HRD intervention (not a principal finding but an insight).

7.3 Implications for management

Knowledge workers are the key drivers of innovation and organisational success (Druker, 1999) and understanding how to position the appropriate technology within their jobs is important to maximise their output (Davenport, 2011). RPA, an emerging technology used to improve effectiveness and efficiencies of staff, is increasing in use year on year by organisations (Agaton & Swedberg, 2018; Lacity et al., 2015). Understanding how to leverage this technology within your organisation is key in order to gain the maximum benefit from it.

This study provides deep insights into RPA's practical application within a knowledge worker context together with how it impacts DE and ITT levels. Firstly, an understanding of the sample is required. The researcher was able to broadly categorise the sample into routine (easy to automate) and abstract tasks (not easy to automate) based on literature (Autor, 2015; Autor & Price, 2013; Davenport, 2011) (refer to Section 2.2.2 for further details). The entire sample of this study was impacted by RPA, as this was a screening question in the data gathering phase of this research. However, as per Table 30, only 16.7% reported their job consisting of only routine tasks, 30.8% reported a mix of routine and abstract tasks and 52.5% reported their job consisting of only abstract tasks.

RPA should be directed towards employees who are involved in work that is of a routine nature or a mixture of routine and abstract tasks as this will allow either partial or complete job redesign resulting in improved autonomy and skill utilisation. Notwithstanding the theoretical drivers of DE (Lloyd, 2008), the absence of a relationship between RPA and DE may in part be due to fact that 52.5% together

with a portion of 30.8% of the research sample performed tasks that were not suitable to an RPA agenda. Additionally, autonomy, which is the key driver of DE (Lloyd, 2008), and a key requirement for knowledge worker productivity (Gambardella et al., 2015) may not be able to be fully realised without management and HRD intervention via a formal job redesign process (Bakker & Demerouti, 2014; Petrou et al., 2018; Tim et al., 2016).

When RPA restructures work (Avasthy, 2019, Davenport & Kirby, 2016; Lacity & Willcocks, 2016; Willcocks et al., 2015) management should undertake a job redesign initiative to ensure that (1) the skill set of the knowledge worker is being properly utilised in the execution of the remaining tasks within a job, something which is achievable since RPA is replacing all of the routine tasks and (2) a higher degree of autonomy is provided to the knowledge worker depending on the type of job that is being performed. As discussed in 6.5.1, RPA does provide an element of autonomy where it may be able to produce information that is required for decision making at a faster rate, however, not to the extent that a job redesign will facilitate. Therefore, the introduction of RPA should be followed by a thorough assessment of the job by management and HRD to identify if a job redesign is required to secure greater autonomy and skill utilisation for the knowledge worker.

The principles of RPA within one's job contributes to reducing ITT. However, the reason why turnover intention reduces is partly due to work being more meaningful (as reported by the partial mediation of meaningfulness on the relationship between RPA and ITT). Therefore, it is imperative that not only autonomy and skill utilisation be considered but also the domains of meaningful work (Bailey et al., 2017) when a job redesign initiative is undertaken by management and HRD. These domains should be exploited where work tasks are redesigned to enhance significance (Hackman & Oldham, 1976; Rosso et al., 2010) and clearly delineated with an element of challenge (Kahn, 1990; May et al., 2004). Work roles should be aligned to the employees' self-image with dignified interactions with others (Bailey et al., 2017) and a degree of congruence should exist between job and person characteristics (Resick et al., 2007). Work interactions with other staff members should be plentiful and encouraged since this creates a sense of belonging, interdependence and value sharing with others as this leads to a common purpose (Lips-Wiersma & Morris, 2009). In sum, redesigned work should also contribute to meaningfulness.

Driving meaningfulness through work should be carefully executed because even though employees may be involved in enriching jobs, management should still demonstrate authenticity when driving the meaningfulness agenda. Meaningfulness should neither be driven in a manner such as emotionally influencing employees to subscribe to an organisational value system that they don't really align to nor should management blur the lines between work and personal life such that work-life balance gets disrupted to tout work meaningfulness when the intent is not. Such management techniques may give rise to existential labour (Bailey et al., 2017), a situation where an employee becomes disconnected from his or her work and the organisation, is inauthentic in agency (both individual and organisational) and experiences dissonance between organisational and personal value systems.

7.4 Suggestions for future research

This study focussed on the impact of RPA on the outcomes of EE (Shuck et al., 2011) and to understand the extent to which meaningfulness, a dimension of EE (Kahn, 1990; May et al., 2004), explained the relationship between RPA and the outcome variables. This study proved that meaningfulness partially mediated the relationship between RPA and ITT and an opportunity exists to test whether the other dimensions of EE (availability and safety) (Kahn, 1990; May et al., 2004) explain the remainder of this relationship that the mediation model in this study did not explain. Furthermore, antecedents to EE have been established in studies by Saks (2006) and Shuck et al. (2011). An opportunity exists to understand how RPA interacts within the framework of antecedents and outcomes of EE.

Contextualising RPA deeper within a job crafting, job design (Petrou et al., 2018; Tim et al., 2016) and JD-R theories (Bakker & Demerouti, 2004) will be beneficial since they all share a commonality – the restructuring of jobs from a task level. Since RPA allows a knowledge worker to restructure tasks within a job, an opportunity exists to test RPA within the formal job crafting framework that's governed by JD-R theory. Therefore, understanding the interplay between job crafting, design and JD-R theory together with RPA will provide insights into how elements like autonomy and skill variety can be optimised, since autonomy and skill variety are prerequisites for knowledge worker performance (Gambardella et al., 2015) DE (Lloyd, 2008) and ITT

(Allen et al., 2010). The link with RPA and DE is of importance since findings from this study proved that RPA has no relationship with DE levels.

Organisational culture (Bailey et al, 2017) contributes to meaningfulness therefore an opportunity exists to understand the interplay between organisational culture and RPA.

This research used a mediated regression analysis to independently test the proposed mediating effect of meaningfulness on the relationship with RPA and DE separately in the presence of one mediator. Structural Equation Modelling offers greater flexibility such that it can test multiple mediators within a model (Preacher & Hayes, 2008) together with testing relationships between constructs simultaneously within a model (Hair, Matthews, Matthews, & Sarstedt, 2017). Using the Partial Least Squares (PLS) approach to SEM, RPA can be potentially tested from an exploratory perspective that it lends itself to, together with multiple constructs including outcomes and mediators simultaneously (Hair et al., 2017, Preacher & Hayes, 2008) to understand the behavioural relationships between these various constructs.

7.5 Limitations of the research

RPA is a relatively new phenomenon with limited academic literature to support it. As discussed in Section 4.9, the largest methodological limitation of this study was the development of the measurement scale for the RPA construct. The researcher subscribed to scale development theory for this process (Carpenter, 2018; Churchill, 1979; Hinkin, 1995; Reidenbach & Robin, 1990; Tay & Jebb, 2016; Worthington & Whittaker, 2016) and where possible, the steps outlined in the scale development process were adhered to. However, time constraints experienced by the researcher for completion of this study prevented the scale from being properly refined from a validity and reliability perspective before final data collection commenced due to the inadequacy of the sample size ($n = 15$) for the pilot testing of the scale.

Knowledge workers in the sample were asked to categorise their jobs according to whether they were routine or abstract in nature. The scale upon which they had to categorise their jobs were made up of descriptions that aligned to either a routine or abstract agenda. 16.7% reported their job consisting of only routine tasks, 30.8% reported a mix of routine and abstract tasks and 52.5% reported their job consisting

of only abstract tasks. There is a probability that this categorisation by the sample in the data collection phase may have been inaccurate such that tasks which are routine and easy to automate may have been classified as abstract and difficult to automate. The researcher relied on this categorisation by the sample to substantiate the findings within this study.

The researcher initially sought to obtain a minimum sample size of 200 respondents that were impacted by RPA within their jobs but a final sample population of 120 was obtained after screening the respondents. Even though the sample size was large enough to prove statistical significance, it was not enough to prove model fit via a CFA, even though differing views in literature existed regarding the minimal sample size for a CFA (Beavers et al., 2013; Hinkin, 1995; Worthington & Whittaker, 2016). As a result, model fit had to be assessed via a PCA.

For the data collection phase of this study the researcher used non-probability sampling incorporating a mix of judgement and snowballing techniques. The researcher was aware of who potential respondents could have been due to the practical experience of the researcher in the field of RPA. Furthermore, snowballing allowed the researcher to reach a wider population through the respondents who were initially identified. Key limitations of a non-probability method are the risk of the sample not being indicative of the target population together with the difficulty of drawing statistical inferences to the wider population due to the inability to measure the sampling error (Wegner, 2016).

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APPENDIX A: Measurement instrument

Online Survey

I am currently a student at the University of Pretoria's Gordon Institute of Business Science and completing my research in partial fulfilment of an MBA. I am conducting research to determine the influence of Robotic Process Automation (RPA) on employee engagement levels of knowledge workers. Please complete the following survey questionnaire to fulfil my research requirements which will take approximately 10-15 minutes to complete. All responses will be anonymous, and all data collected from the questionnaire will be kept confidential. By completing the questionnaire, you are indicating that your participation is voluntary, however you may exit the questionnaire at any time without penalty. Should you have any questions please contact myself or my research supervisor on the details below.

Researcher: Kushal Singh

Contact Details: kush.singh@angloamerican.com

Supervisor: Manoj Chiba

Contact details: ChibaM@gibs.co.za

Part A: Descriptive. Please tick the appropriate block.

Tasks within your job impacted by RPA?	
Yes	
No	

Age	
20-29	
30-39	
40-49	
50-59	
Over 60	

Job Level	
Junior Staff	
Team Lead	
Specialist	
Middle Manager	
Senior Manager	
Executive	
Other	
Education Level	
Matric	
Diploma	
Bachelor's degree	
Honours Degree	
Master's degree	
PhD	
Professional Designation (e.g. CA(SA))	
Please specify professional designation	

Length of Service	
Less than 1 year	
Between 1 and 5 years	
Between 5 and 10 years	
More than 10 years	

Industry	
Agriculture	
Construction	
Education	
Finance	
Fishing	
Forestry	
Hospitality	
Manufacturing	
Mining	
Telecommunications	
Transportation	
Utilities electricity or water)	
Other	

Which of the following sentences best describes your current daily work?

(Please, choose from 1 to 2 answers)

Routine work.

Relies on formal rules, procedures, and training

Systematic, repeatable work

Relies on formal processes, methodologies, or standards

Improvisational work

Highly reliant on deep expertise across multiple functions

Judgment-oriented work

Relies on individual expertise and experience

Part B: Indicate the extent of the following where **1 equals strongly disagree** and **7 strongly agree**.

1. Meaningfulness	1	2	3	4	5	6	7
The work I do on this job is very important to me.							
My job activities are personally meaningful to me.							
The work I do on this job is worthwhile.							
My job activities are significant to me.							
The work I do on this job is meaningful to me.							
I feel that the work I do on this job is valuable.							

2. Psychological Climate	1	2	3	4	5	6	7
My boss is flexible about how I accomplish my job objectives.							
My manager is supportive of my ideas and ways of getting things done.							
My boss gives me the authority to do my job as I see fit.							
I'm careful in taking responsibility because my boss is often critical of new ideas. [reverse scored]							
I can trust my boss to back me up on decisions I make in the field.							
I feel very useful in my job.							
Doing my job well really makes a difference.							
I feel like a key member of the organization.							
The work I do is very valuable to the organization.							
I rarely feel my work is taken for granted.							
My supervisors generally appreciate the way I do my job.							
The organization recognizes the significance of the contributions I make.							
My job is very challenging.							
It takes all my resources to complete my work objectives.							

3. Affective Commitment	1	2	3	4	5	6	7
I feel a strong sense of belonging to my organization.							
I feel personally attached to my work organization.							
I am proud to tell others I work at my organization.							
Working at my organization has a great deal of personal meaning to me.							
I would be happy to work at my organization until I retire.							
I really feel that problems faced by my organization are also my problems.							

4. Discretionary Effort	1	2	3	4	5	6	7
When I work, I really exert myself to the fullest, beyond that what is expected.							
I finish a job even if it means sacrificing breaks or lunches.							
I do more than is expected of me.							
I voluntarily put in extra hours to achieve a result faster.							
I persist in overcome obstacles to complete an important task.							
I put in extra effort when I find it necessary.							
I work harder than expected to help my organization be successful.							

5. Intention to Turnover	1	2	3	4	5	6	7
I frequently think of quitting my job.							
I am planning to search for a new job during the next 12 months.							
If I have my own way, I will be working for this organization one year from now. [reversed scored]							

Robotic Process Automation (RPA) is described as the use of computer software that is designed to execute high-volume, routine or repetitive tasks within a job that were previously performed by a human.

6. RPA	1	2	3	4	5	6	7
Routine or repetitive tasks within my job have been replaced with RPA.							
RPA enables me to accomplish my overall job objectives more effectively.							
RPA allows me to spend more time on what I was employed to do. – REMOVED							
RPA allows me to be more creative and innovative because my routine and repetitive tasks have been replaced by RPA.							
RPA improves my job performance. – REMOVED							
RPA improves my job productivity.							
RPA improves my job effectiveness.							
RPA makes it easier to do my job. – REMOVED							
RPA allows me to spend more time on analysis, add value and make better job decisions. – REMOVED							

*Refer to Appendix C for further detail on RPA measurement scale

APPENDIX B: Correlations

Table 31: Correlations

Correlations						
		RPA	Meaningfulness	Discretionary Effort	Intention to Turnover	
Spearman's rho	RPA	Correlation Coefficient	1,000	.231*	-0,042	-.228*
		Sig. (2-tailed)		0,011	0,651	0,012
		N	120	120	120	120
	Meaningfulness	Correlation Coefficient	.231*	1,000	.511**	-.391**
		Sig. (2-tailed)	0,011		0,000	0,000
		N	120	120	120	120
	Discretionary Effort	Correlation Coefficient	-0,042	.511**	1,000	-.226*
		Sig. (2-tailed)	0,651	0,000		0,013
		N	120	120	120	120
	Intention to Turnover	Correlation Coefficient	-.228*	-.391**	-.226*	1,000
		Sig. (2-tailed)	0,012	0,000	0,013	
		N	120	120	120	120
*, Correlation is significant at the 0.05 level (2-tailed).						
**, Correlation is significant at the 0.01 level (2-tailed).						

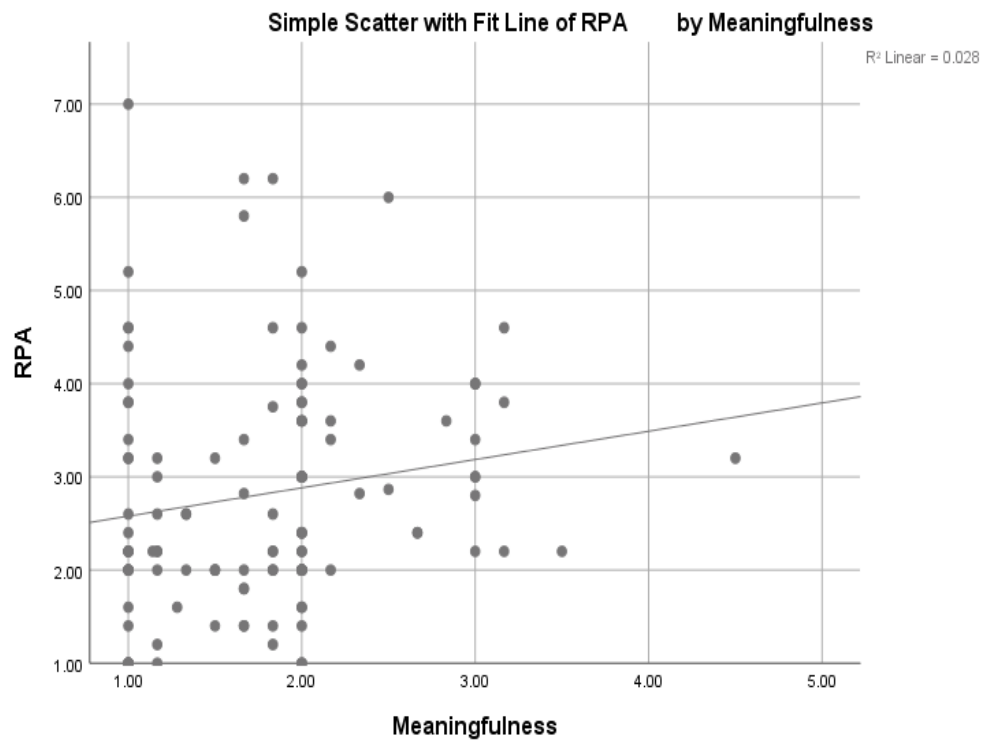


Figure 13: Scatter plot: meaningfulness and RPA

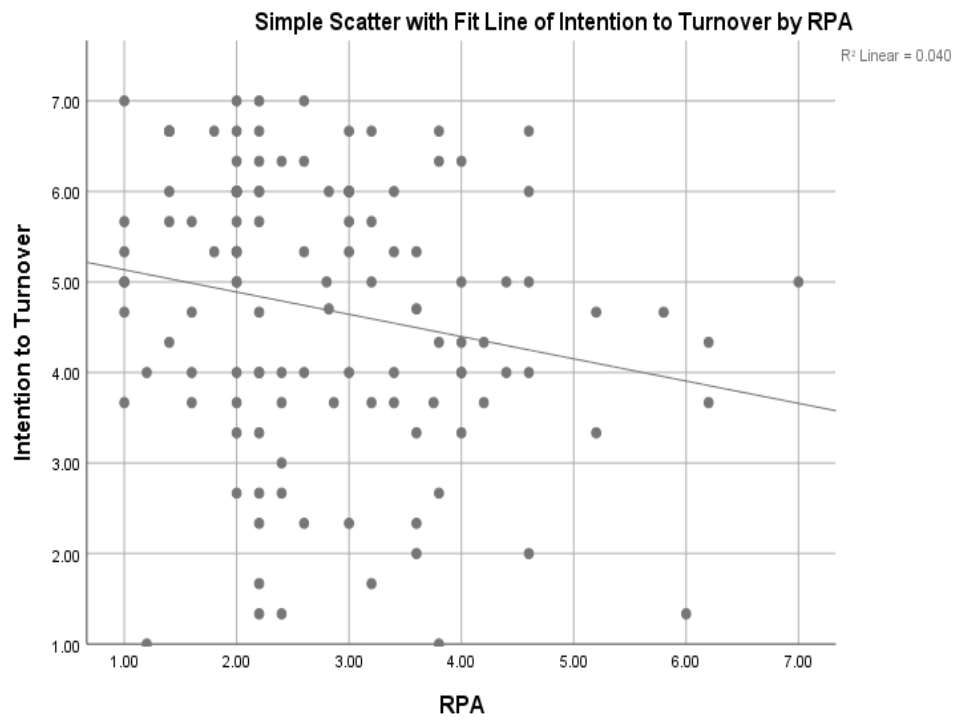


Figure 14: Scatter plot: RPA and ITT

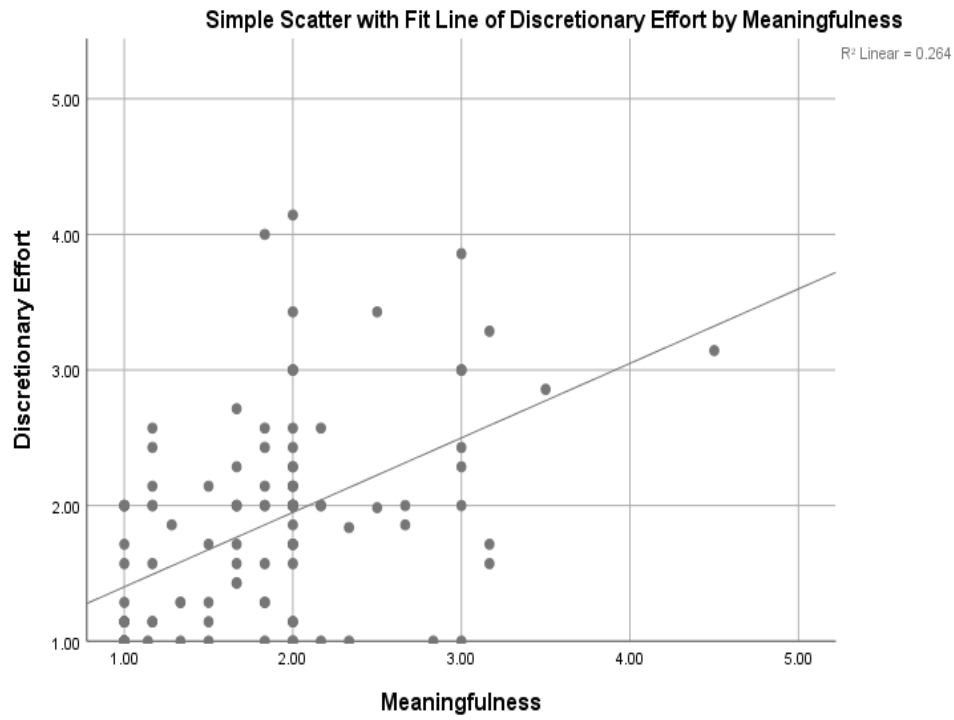


Figure 15: Scatter plot: meaningfulness and DE

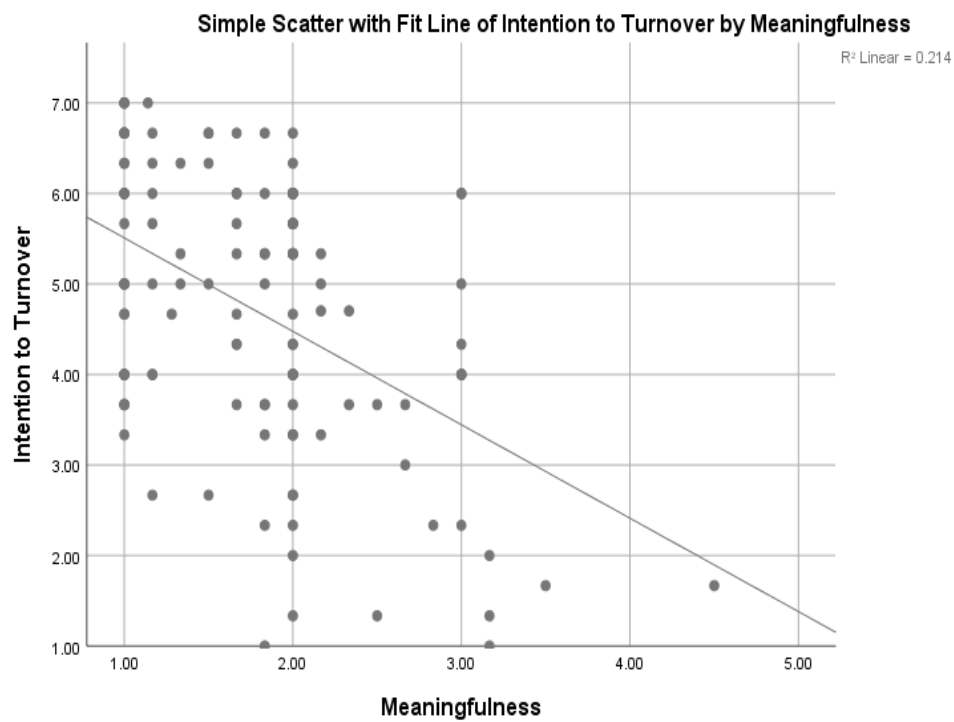


Figure 16: Scatter plot: meaningfulness and ITT

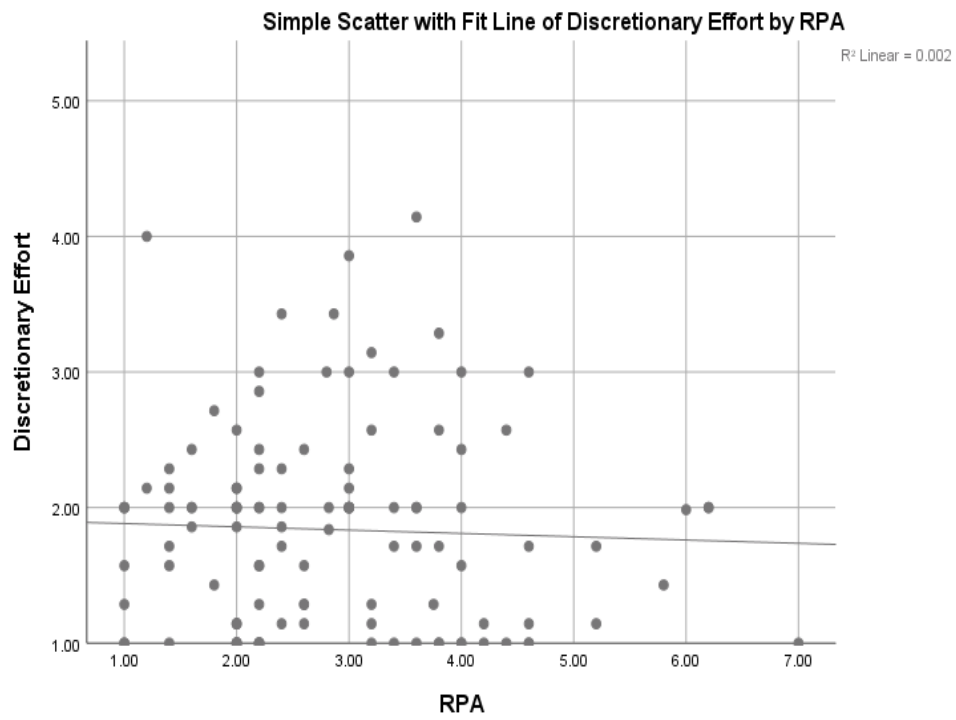


Figure 17: Scatter plot: RPA and DE

APPENDIX C: Reliability (RPA)

Table 32: RPA scale adjustment: reliability

Item-Total Statistics				
	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
RPA1	21,5431	122,542	0,375	0,978
RPA2	22,1363	110,008	0,857	0,955
RPA3	22,1278	105,884	0,908	0,952
RPA4	22,0875	107,920	0,859	0,955
RPA5	22,0855	106,636	0,926	0,951
RPA6	22,1644	108,761	0,901	0,953
RPA7	22,2072	109,024	0,904	0,953
RPA8	22,2126	108,797	0,934	0,952
RPA9	22,2211	107,793	0,928	0,952

*Highlighted items denote most appropriate items for removal

Table 33: Revised reliability for RPA scale

Cronbach's Alpha	N of Items			
0,885	5			
Item-Total Statistics				
	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
RPA1	10,7973	29,608	0,366	0,941
RPA2	11,3906	24,372	0,832	0,836
RPA4	11,3417	23,683	0,809	0,840
RPA6	11,4187	24,276	0,838	0,834
RPA7	11,4614	24,433	0,839	0,834

*Revised alpha score after adjustment: 0.885 (0.89 rounded) with 5 items

APPENDIX D: Validity

Table 34: Validity: meaningfulness

		Correlations																				
		Mean1	Mean2	Mean3	Mean4	Mean5	Mean6	DE1	DE2	DE3	DE4	DE5	DE6	DE7	ITT1	ITT2	ITT3rc	RPA1	RPA2	RPA4	RPA6	RPA7
Mean1	Pearson Correlation	1	.576**	.705**	.685**	.683**	.595**	.356**	.295**	.336**	.357**	.462**	.359**	.334**	-.388**	-.340**	-.374**	-0,014	0,064	0,133	0,066	0,108
	Sig. (2-tailed)		0,000	0,000	0,000	0,000	0,000	0,000	0,001	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,882	0,489	0,147	0,475	0,241
	N	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120
Mean2	Pearson Correlation	.576**	1	.643**	.721**	.782**	.395**	.388**	.246**	.322**	.374**	.345**	.250**	.326**	-.329**	-.234**	-.314**	0,054	0,071	0,104	0,036	0,027
	Sig. (2-tailed)	0,000		0,000	0,000	0,000	0,000	0,000	0,007	0,000	0,000	0,000	0,006	0,000	0,000	0,010	0,000	0,555	0,442	0,260	0,696	0,771
	N	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120
Mean3	Pearson Correlation	.705**	.643**	1	.860**	.814**	.622**	.436**	.399**	.357**	.386**	.567**	.491**	.389**	-.401**	-.346**	-.363**	-0,025	.204	.262**	.196	.209
	Sig. (2-tailed)	0,000	0,000		0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,787	0,025	0,004	0,032	0,022
	N	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120
Mean4	Pearson Correlation	.685**	.721**	.860**	1	.887**	.556**	.394**	.306**	.333**	.326**	.466**	.394**	.361**	-.355**	-.315**	-.436**	-0,040	0,105	.209	0,133	0,108
	Sig. (2-tailed)	0,000	0,000	0,000		0,000	0,000	0,000	0,001	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,665	0,255	0,022	0,149	0,241
	N	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120
Mean5	Pearson Correlation	.683**	.782**	.814**	.887**	1	.555**	.355**	.300**	.323**	.328**	.466**	.376**	.293**	-.400**	-.349**	-.459**	0,030	0,158	.233	0,158	0,161
	Sig. (2-tailed)	0,000	0,000	0,000	0,000		0,000	0,000	0,001	0,000	0,000	0,000	0,000	0,001	0,000	0,000	0,000	0,748	0,086	0,010	0,084	0,079
	N	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120
Mean6	Pearson Correlation	.595**	.395**	.622**	.556**	.555**	1	.284**	.424**	.231	.266**	.503**	.422**	.248**	-.203	-0,106	-0,164	0,057	.228	.240**	.217	.249**
	Sig. (2-tailed)	0,000	0,000	0,000	0,000	0,000		0,002	0,000	0,011	0,003	0,000	0,000	0,006	0,026	0,250	0,074	0,534	0,012	0,008	0,017	0,006
	N	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120

Table 35: Validity: DE

		Correlations																				
		Mean1	Mean2	Mean3	Mean4	Mean5	Mean6	DE1	DE2	DE3	DE4	DE5	DE6	DE7	ITT1	ITT2	ITT3rc	RPA1	RPA2	RPA4	RPA6	RPA7
DE1	Pearson Correlation	.356**	.388**	.436**	.394**	.355**	.284**	1	.579**	.705**	.756**	.517**	.411**	.645**	-.325**	-.233**	-.402**	0.062	-0.084	-0.102	-0.086	-0.088
	Sig. (2-tailed)	0.000	0.000	0.000	0.000	0.000	0.002		0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.010	0.000	0.502	0.361	0.265	0.349	0.338
	N	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120
DE2	Pearson Correlation	.295**	.246**	.399**	.306**	.300**	.424**	.579**	1	.439**	.566**	.545**	.472**	.365**	-.260**	-.303**	-.250**	-0.086	-0.081	-0.002	-0.018	0.008
	Sig. (2-tailed)	0.001	0.007	0.000	0.001	0.001	0.000	0.000		0.000	0.000	0.000	0.000	0.000	0.004	0.001	0.006	0.352	0.381	0.983	0.841	0.934
	N	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120
DE3	Pearson Correlation	.336**	.322**	.357**	.333**	.323**	.231**	.705**	.439**	1	.845**	.641**	.516**	.717**	-.208**	-0.142	-.237**	0.014	-0.106	-0.089	-0.104	-0.092
	Sig. (2-tailed)	0.000	0.000	0.000	0.000	0.000	0.011	0.000	0.000		0.000	0.000	0.000	0.000	0.022	0.122	0.009	0.876	0.247	0.335	0.256	0.320
	N	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120
DE4	Pearson Correlation	.357**	.374**	.386**	.326**	.328**	.266**	.756**	.566**	.845**	1	.623**	.491**	.681**	-.310**	-.255**	-.293**	0.010	-0.094	-0.048	-0.111	-0.092
	Sig. (2-tailed)	0.000	0.000	0.000	0.000	0.000	0.003	0.000	0.000	0.000		0.000	0.000	0.000	0.001	0.005	0.001	0.910	0.306	0.601	0.229	0.317
	N	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120
DE5	Pearson Correlation	.462**	.345**	.567**	.466**	.466**	.503**	.517**	.545**	.641**	.623**	1	.782**	.521**	-0.169	-0.110	-0.157	-0.020	0.066	0.091	0.079	0.099
	Sig. (2-tailed)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000		0.000	0.000	0.066	0.233	0.086	0.830	0.473	0.321	0.391	0.282
	N	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120
DE6	Pearson Correlation	.359**	.250**	.491**	.394**	.376**	.422**	.411**	.472**	.516**	.491**	.782**	1	.517**	-0.057	-0.019	-.222**	-0.050	0.127	0.089	0.103	0.088
	Sig. (2-tailed)	0.000	0.006	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000		0.000	0.539	0.835	0.015	0.586	0.165	0.335	0.261	0.338
	N	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120
DE7	Pearson Correlation	.334**	.326**	.389**	.361**	.293**	.248**	.645**	.365**	.717**	.681**	.521**	.517**	1	-.252**	-0.095	-.268**	-0.053	-0.094	-0.020	-0.013	-0.015
	Sig. (2-tailed)	0.000	0.000	0.000	0.000	0.001	0.006	0.000	0.000	0.000	0.000	0.000	0.000		0.005	0.303	0.003	0.565	0.308	0.828	0.891	0.868
	N	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120

Table 36: Validity: ITT

		Correlations																				
		Mean1	Mean2	Mean3	Mean4	Mean5	Mean6	DE1	DE2	DE3	DE4	DE5	DE6	DE7	ITT1	ITT2	ITT3rc	RPA1	RPA2	RPA4	RPA6	RPA7
ITT1	Pearson Correlation	-.388**	-.329**	-.401**	-.355**	-.400**	-.203*	-.325**	-.260**	-.208*	-.310**	-.0169	-.057	-.252**	1	.673**	.462**	-.033	-.066	-.0137	-.046	-.081
	Sig. (2-tailed)	0,000	0,000	0,000	0,000	0,000	0,026	0,000	0,004	0,022	0,001	0,066	0,539	0,005		0,000	0,000	0,724	0,473	0,136	0,617	0,377
	N	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120
ITT2	Pearson Correlation	-.340**	-.234*	-.346**	-.315**	-.349**	-.0106	-.233*	-.303**	-.0142	-.255**	-.0110	-.019	-.095	.673**	1	.485**	-.223*	-.0149	-.213*	-.066	-.099
	Sig. (2-tailed)	0,000	0,010	0,000	0,000	0,000	0,250	0,010	0,001	0,122	0,005	0,233	0,835	0,303	0,000		0,000	0,014	0,105	0,020	0,471	0,280
	N	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120
ITT3rc	Pearson Correlation	-.374**	-.314**	-.363**	-.436**	-.459**	-.0164	-.402**	-.250**	-.237**	-.293**	-.0157	-.222*	-.268**	.462**	.485**	1	-0,007	-.224*	-.244**	-.241**	-.228*
	Sig. (2-tailed)	0,000	0,000	0,000	0,000	0,000	0,074	0,000	0,006	0,009	0,001	0,086	0,015	0,003	0,000	0,000		0,935	0,014	0,007	0,008	0,012
	N	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120

Table 37: Validity: RPA

		Correlations																				
		Mean1	Mean2	Mean3	Mean4	Mean5	Mean6	DE1	DE2	DE3	DE4	DE5	DE6	DE7	ITT1	ITT2	ITT3rc	RPA1	RPA2	RPA4	RPA6	RPA7
RPA1	Pearson Correlation	-0,014	0,054	-0,025	-0,040	0,030	0,057	0,062	-0,086	0,014	0,010	-0,020	-0,050	-0,053	-0,033	-.223*	-0,007	1	.478**	.346**	.261**	.263**
	Sig. (2-tailed)	0,882	0,555	0,787	0,665	0,748	0,534	0,502	0,352	0,876	0,910	0,830	0,586	0,565	0,724	0,014	0,935		0,000	0,000	0,004	0,004
	N	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120
RPA2	Pearson Correlation	0,064	0,071	.204*	0,105	0,158	.228*	-0,084	-0,081	-0,106	-0,094	0,066	0,127	-0,094	-0,066	-0,149	-.224*	.478**	1	.742**	.759**	.763**
	Sig. (2-tailed)	0,489	0,442	0,025	0,255	0,086	0,012	0,361	0,381	0,247	0,306	0,473	0,165	0,308	0,473	0,105	0,014	0,000		0,000	0,000	0,000
	N	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120
RPA4	Pearson Correlation	0,133	0,104	.262**	.209*	.233*	.240**	-0,102	-0,002	-0,089	-0,048	0,091	0,089	-0,020	-0,137	-.213*	-.244**	.346**	.742**	1	.804**	.799**
	Sig. (2-tailed)	0,147	0,260	0,004	0,022	0,010	0,008	0,265	0,983	0,335	0,601	0,321	0,335	0,828	0,136	0,020	0,007	0,000	0,000		0,000	0,000
	N	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120
RPA6	Pearson Correlation	0,066	0,036	.196*	0,133	0,158	.217*	-0,086	-0,018	-0,104	-0,111	0,079	0,103	-0,013	-0,046	-0,066	-.241**	.261**	.759**	.804**	1	.950**
	Sig. (2-tailed)	0,475	0,696	0,032	0,149	0,084	0,017	0,349	0,841	0,256	0,229	0,391	0,261	0,891	0,617	0,471	0,008	0,004	0,000	0,000		0,000
	N	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120
RPA7	Pearson Correlation	0,108	0,027	.209*	0,108	0,161	.249**	-0,088	0,008	-0,092	-0,092	0,099	0,088	-0,015	-0,081	-0,099	-.228*	.263**	.763**	.799**	.950**	1
	Sig. (2-tailed)	0,241	0,771	0,022	0,241	0,079	0,006	0,338	0,934	0,320	0,317	0,282	0,338	0,868	0,377	0,280	0,012	0,004	0,000	0,000	0,000	
	N	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120	120
**. Correlation is significant at the 0.01 level (2-tailed).																						
*. Correlation is significant at the 0.05 level (2-tailed).																						

APPENDIX E: Measured variables

Table 38: Measured variables

Descriptive Statistics				
		N	Mean	Std. Deviation
The work I do at my job is very important to me.	Mean1	120	1,7000	0,78430
My job activities are personally meaningful to me.	Mean2	120	1,9083	0,94376
The work I do at my job is worthwhile.	Mean3	120	1,8487	0,74064
My job activities are significant to me.	Mean4	120	1,8403	0,81975
The work I do at my job is meaningful to me.	Mean5	120	1,8403	0,86949
I feel that the work I do at my job is valuable.	Mean6	120	1,6417	0,63240
When I work, I exert myself to the fullest, beyond that which is expected.	DE1	120	1,9748	1,02459
I finish a job even if it means sacrificing breaks or lunches.	DE2	120	1,8739	0,95754
I do more than is expected of me.	DE3	120	1,8898	0,98547
I voluntarily put in extra hours to achieve a result faster.	DE4	120	1,8655	0,96078
I persist in overcoming obstacles to complete an important task.	DE5	120	1,6891	0,73046
I put in extra effort when I find it necessary.	DE6	120	1,6303	0,69652
I work harder than is expected to help my organisation be successful.	DE7	120	1,9412	0,98981
I frequently think of quitting my job.	ITT1	120	4,6525	1,76510
I am planning to search for a new job during the next 12 months.	ITT2	120	4,3390	1,93691
If I have my own way, I will be working for this organisation one year from now.	ITT3rc	120	5,0686	1,79041
Routine or repetitive tasks within my job have been replaced by RPA.	RPA1	120	3,3051	1,57985
RPA enables me to accomplish my overall job objectives more effectively.	RPA2	120	2,7119	1,45002
RPA allows me to spend more time on what I was actually employed to do.	RPA3	120	2,7203	1,59245
I have the time to be more creative and innovative because my routine and repetitive tasks have been replaced by RPA.	RPA4	120	2,7607	1,55919
RPA improves my job performance.	RPA5	120	2,7627	1,52667
RPA improves my job productivity.	RPA6	120	2,6838	1,45319
RPA improves my job effectiveness.	RPA7	120	2,6410	1,43463
RPA makes it easier for me to do my job.	RPA8	120	2,6356	1,40626
RPA allows me to spend more time on analysis or other activities that result in better decision making.	RPA9	120	2,6271	1,46555
	Valid N (listwise)	120		

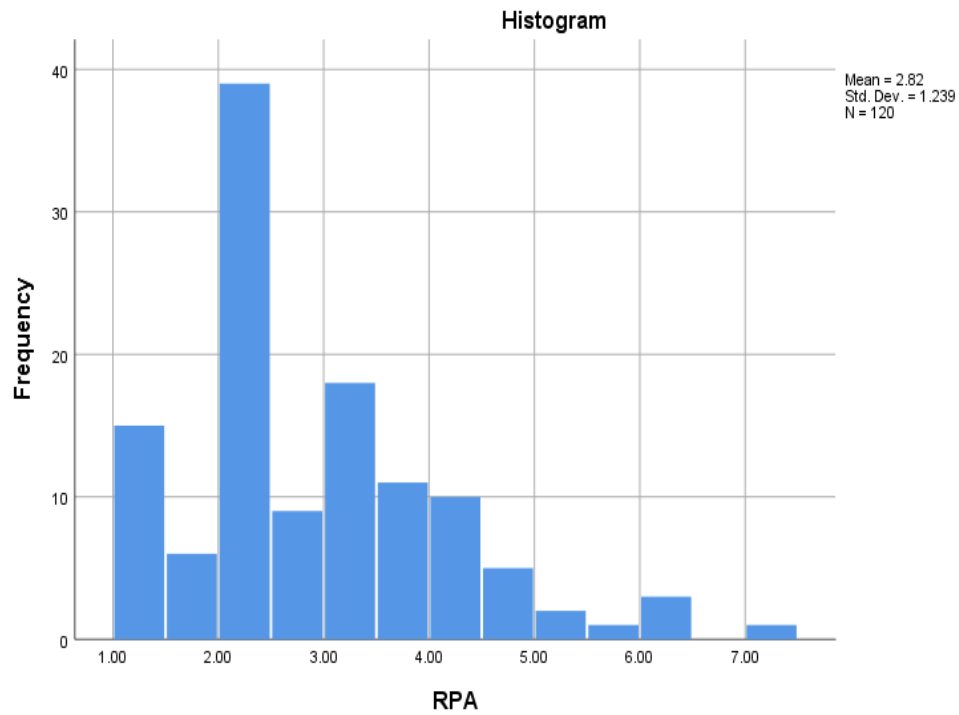


Figure 18: Histogram: RPA

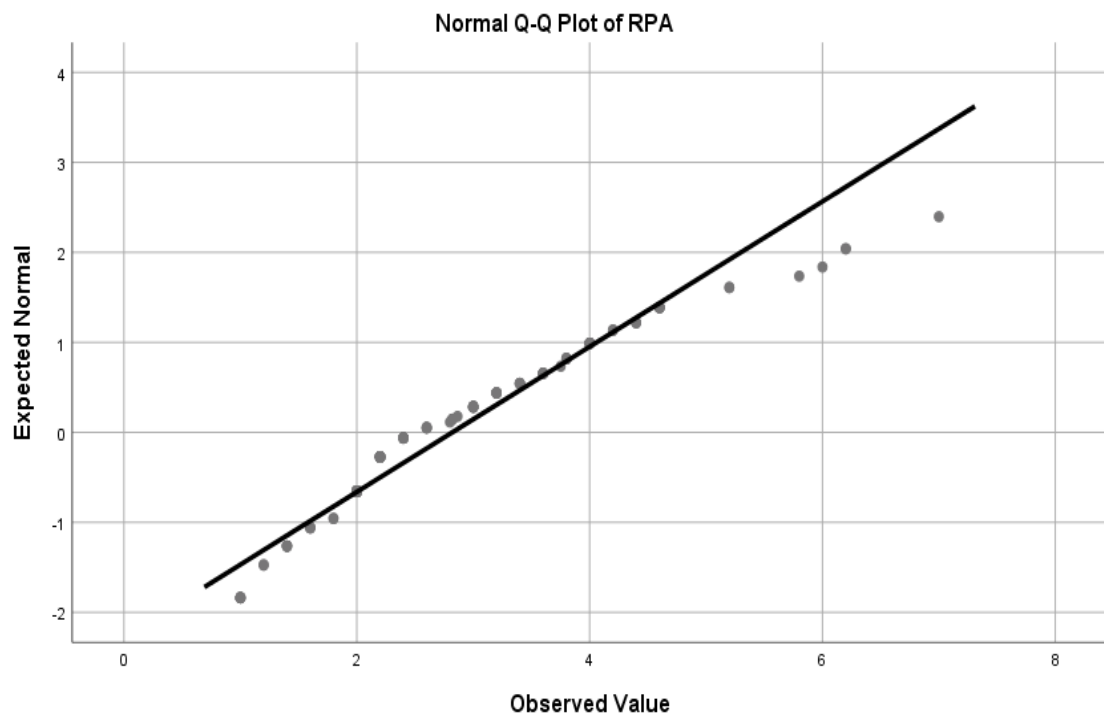


Figure 19: Q-Q plot: RPA

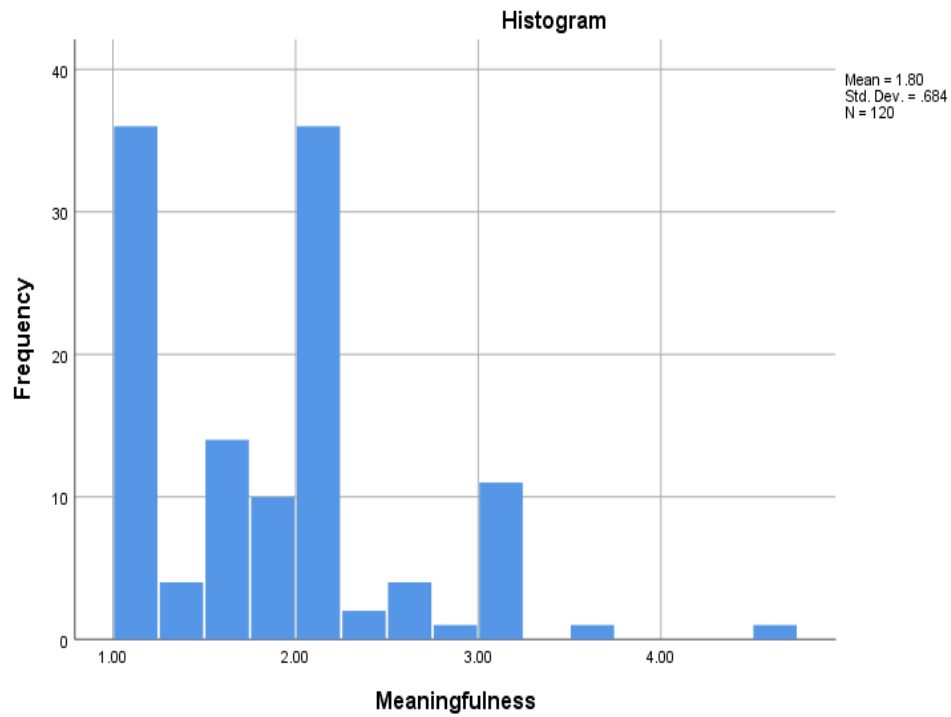


Figure 20: Histogram: meaningfulness

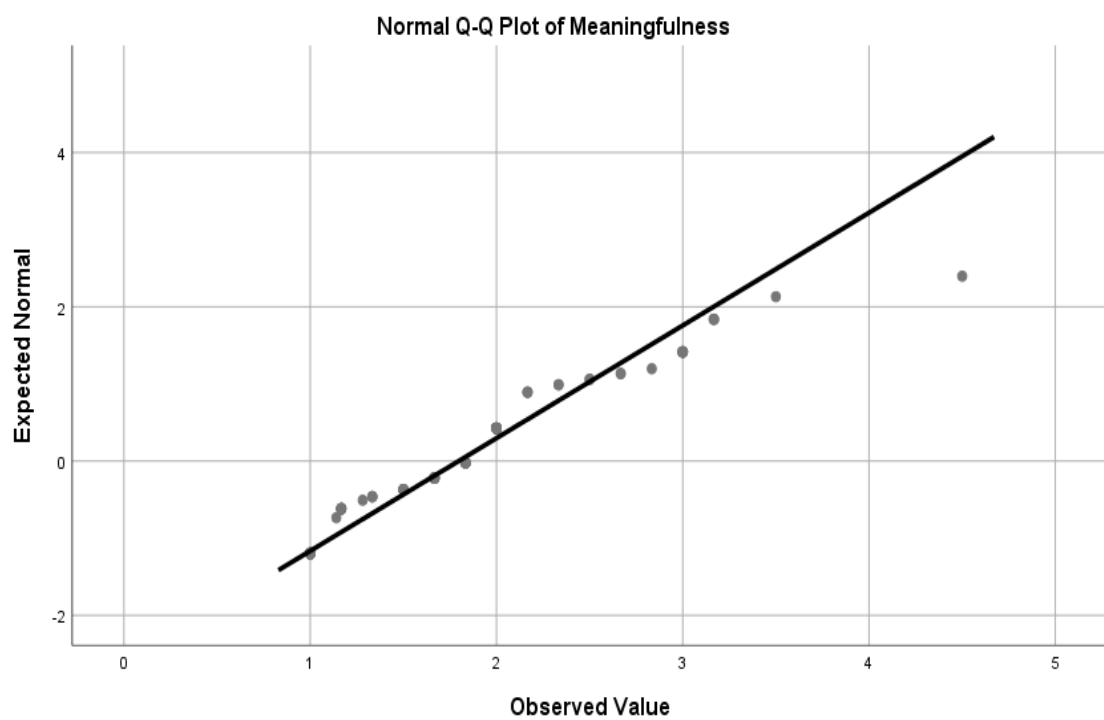


Figure 21: Q-Q plot: meaningfulness

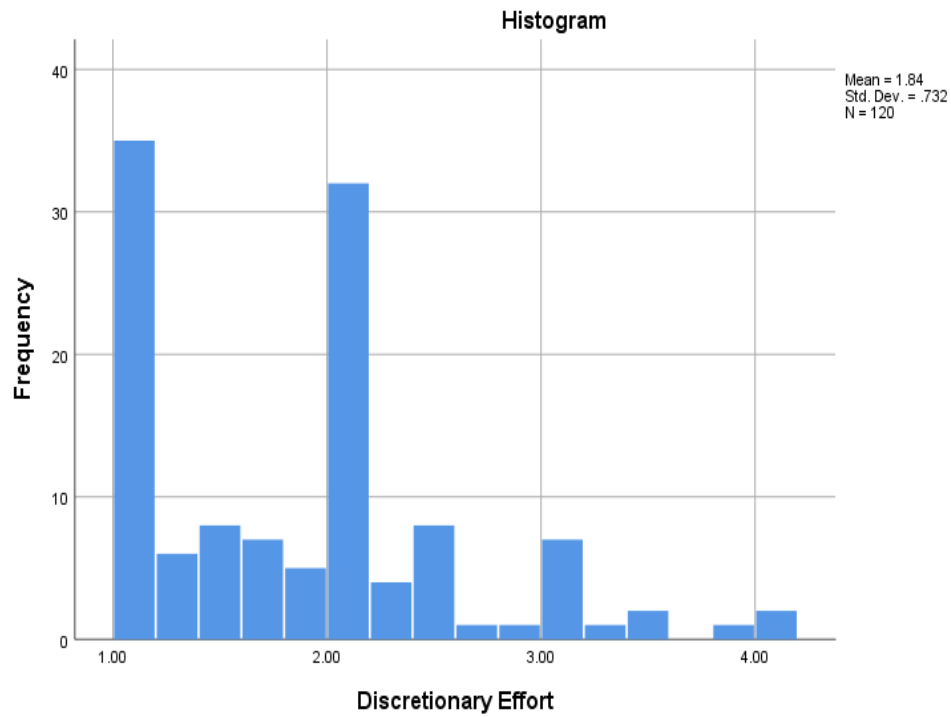


Figure 22: Histogram: DE

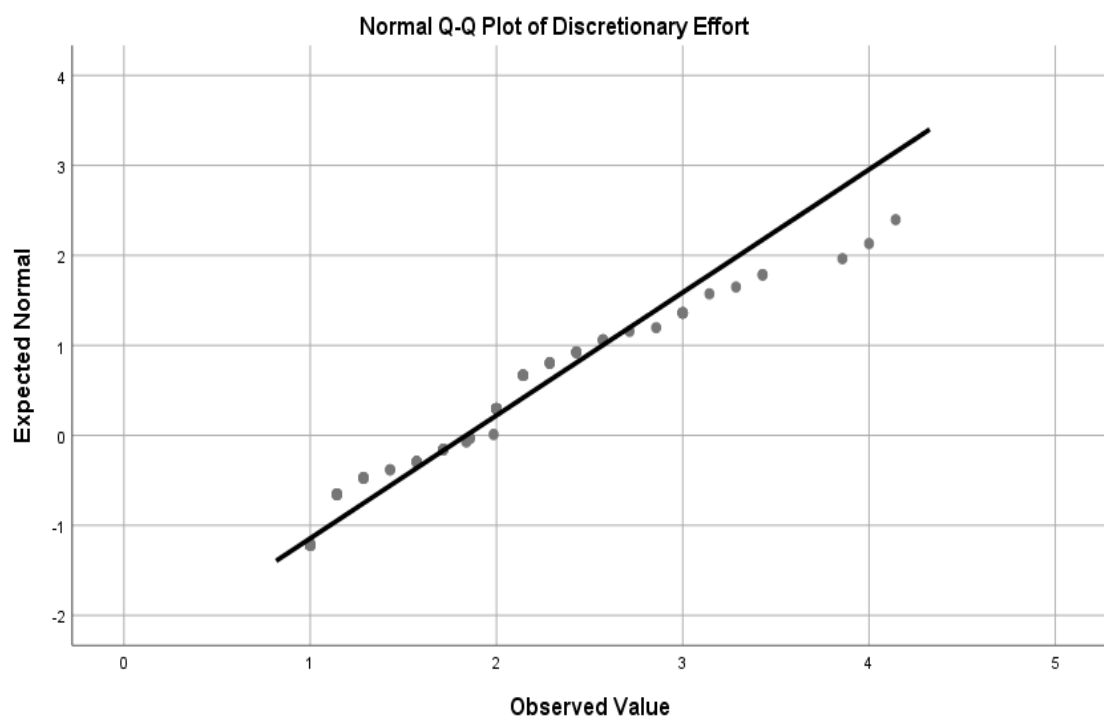


Figure 23: Q-Q plot: DE

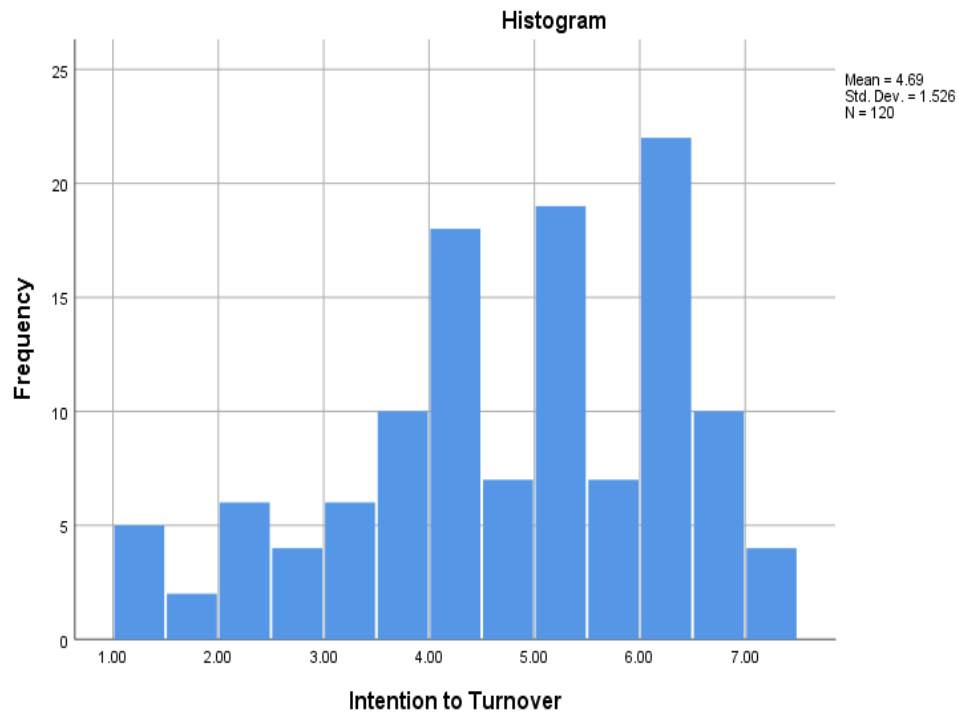


Figure 24: Histogram: ITT

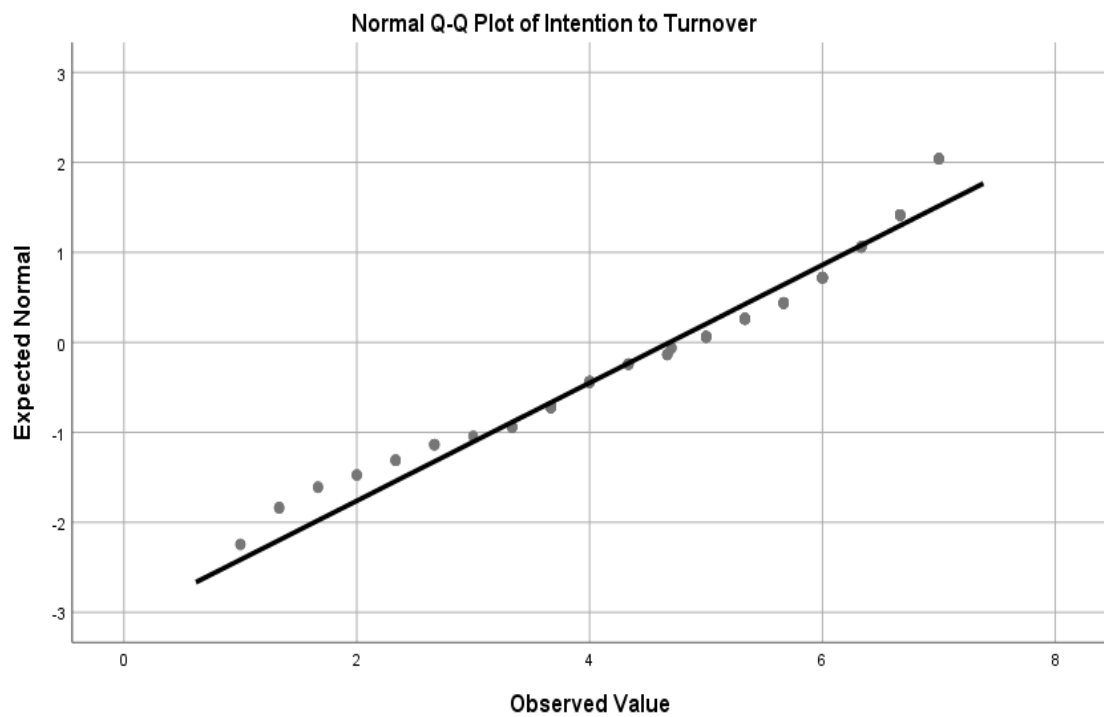


Figure 25: Q-Q plot: ITT

APPENDIX F: Factor analysis

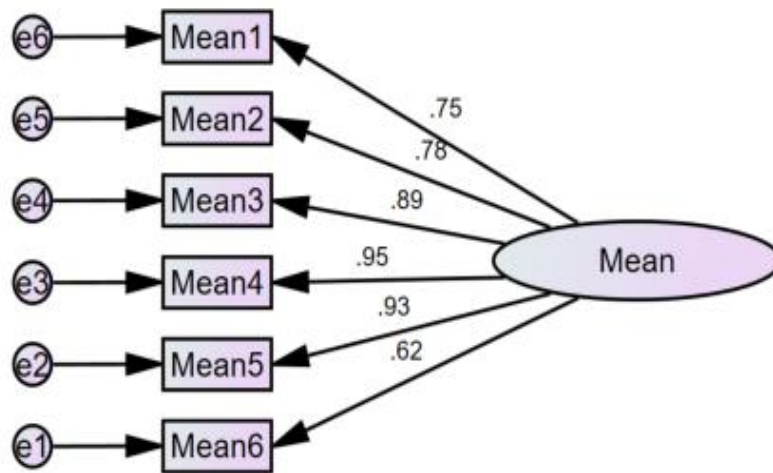


Figure 26: Factor loadings: meaningfulness

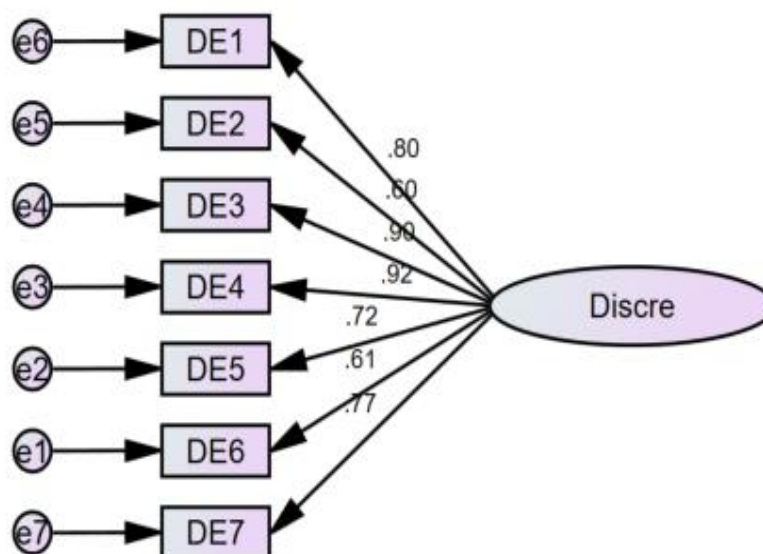


Figure 27: Factor loadings: DE

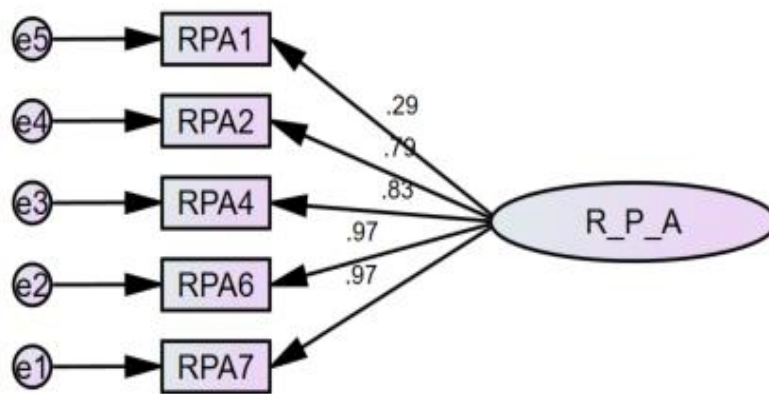


Figure 28: Factor loadings: RPA